When Flexibility Becomes Forbearance: Payment-in-Kind in Private Credit

Paul Rintamäki Sascha Steffen

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Abstract

Payment-in-Kind (PIK) provisions allow borrowers to capitalize unpaid interest into the loan principal, providing financial flexibility but potentially enabling forbearance to insolvent firms. Using comprehensive Business Development Company (BDC) loan data, we show PIK is predominantly used by distressed borrowers. PIK usage predicts persistent credit deterioration and outcomes are significantly worse when borrowers exercise PIK options ex-post compared to structuring PIK at origination. We document that private equity sponsorship mitigates deterioration, while PIK usage results in maturity extensions rather than loan restructurings, consistent with forbearance. Despite substantial bank lending to BDCs, covenant restrictions insulate banks from PIK-related losses, thereby increasing financial constraints and reducing credit supply of BDCs to middle-market firms.

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* First Version: April 2025. Both authors are at Frankfurt School of Finance & Management, Adickesallee 32-34. 60322 Frankfurt, Germany. Contact details: p.rintamaki@fs.de (Rintamäki) and s.steffen@fs.de (Steffen). We greatly appreciate support from the Centre for European Transformation. We thank James Albertus (discussant), Bo Becker, Tobias Berg, Harald Hau, Maximilian Jager, Jun Quian, Daniel Streitz, and participants at Peking University Guanghu School of Business, Fudan International School of Finance, City University Hong Kong, National University of Singapore, Singapore Management University, the ESRB Expert Group on Nonbank Financial Intermediation, DNB, University of Amsterdam, Northern Finance Association 2025 meeting, Frankfurt School of Finance & Management, Private Equity Research Consortium (PERC) 2025 Symposium, Federal Reserve Day-Ahead conference for valuable comments and suggestions. An earlier version of the paper was circulated under the title "PIK now and pay later - How deferred interest reshapes private credit".

1 Introduction

Payment-in-Kind (PIK) provisions allow borrowers to defer cash interest payments by rolling unpaid interest onto the outstanding loan principal. The theoretical framework for such provisions is well-established: contingent liquidity is valuable when external financing is costly (Holmstrom and Tirole, 1997; Gamba and Triantis, 2008), particularly when borrowers face transitory cash flow shocks but remain fundamentally solvent.[1] PIK provisions can thus serve a role similar to bank revolving credit facilities – providing contingent liquidity in markets where bank access is limited.

Yet contractual flexibility can also enable lenders to delay loss recognition. A large literature documents that weakly capitalized banks extend credit to insolvent borrowers – so-called zombie lending – to avoid writing down their loans (Peek and Rosengren, 2005; Caballero et al., 2008; Acharya et al., 2019). In this literature, capital constraints give undercapitalized banks incentives to evergreen distressed exposures. PIK provisions raise an analogous question in private credit markets. Unlike bank zombie lending, however, PIK embeds the flexibility to defer loss recognition directly in the loan contract – enabling forbearance without any capital constraint of the lender.[2]

We study this question using the universe of Business Development Company (BDC) lending – the largest identifiable segment of U.S. private credit – which provides quarterly loan-level observations including PIK usage, fair value assessments, and non-accrual classifications for every loan from the 2012 to 2024 period.[3] To distinguish between efficient liquidity provision and zombie lending, we ask three questions. First, what determines

[1]A large literature in finance has discussed the value of financial flexibility for non-finanical firms. For example, financial flexibility is valuable when external funding is costly (Giambona et al., 2025), during crises when capital markets funding is unavailable (Campello et al., 2010; Acharya and Steffen, 2020; Fahlenbrach et al., 2021) or fixed costs are high (Barry et al., 2022), and to avoid costly financial distress and underinvestment (Bonaimé et al., 2014).

[2]The widespread use of PIK provisions has generated considerable debate among practitioners and policymakers. See e.g. "The rise and risks of private credit" by IMF (2024), "Why 'Payment-In-Kind' Debt Is So Appealing - and Risky" (Bloomberg, Nov 2025) or "Corporate debts mount as credit funds let borrowers defer payments" (Financial Times, Oct 2024).

[3]BDCs are closed-end investment funds lending primarily to middle-market firms. As of Q4 2024, they manage USD 441 billion in total assets and USD 417 billion in investments, representing a substantial share of U.S. private credit. We list all BDCs in our sample in the Online Appendix.

PIK usage? Identifying the borrower characteristics and circumstances surrounding PIK usage reveals whether it targets temporarily distressed but viable firms or fundamentally insolvent borrowers. Second, does borrower performance improve or deteriorate following PIK usage? If PIK bridges temporary liquidity shortfalls, borrowers should improve as financial constraints ease. Third, how do banks respond to the use of PIK options in BDC portfolios? Given banks' growing exposure to BDCs and potential spillover risks (Acharya et al., 2024), we examine whether banks enable PIK provision through credit lines or restrict financing to PIK-heavy BDCs. Bank credit supply to PIK-active BDCs reveals whether banks view PIK as value-enhancing flexibility or problematic forbearance. Our key contribution is to document that PIK provisions function primarily as contract-embedded forbearance mechanisms rather than efficient liquidity tools.

We build a novel and comprehensive loan-level dataset that covers the full universe of BDC lending from 2012 onwards. The novelty of our dataset is the ability to track each loan quarterly from origination until either maturity, write-off, or sale by the BDC. Moreover, it lets us distinguish between different types of PIK loans. While some borrowers defer interest payments immediately after origination (so-called "PIK notes"), we show that in recent years the market has shifted toward loans that include a "PIK toggle" that allows borrowers to exercise this option at some later point during the loan's lifecycle. We show that at origination, these loans exhibit significantly different characteristics: PIK-notes have higher interest rates, shorter maturity, are typically structured as subordinated debt with a fixed interest rate, and are frequently coupled with equity stakes for the lenders. In contrast, loans that use PIK toggles are more similar to loans that do not exhibit PIK use at all. These loans are typically first lien senior secured with floating rates and longer maturities.

We next study the timing and circumstances under which borrowers use PIK Toggles, exploiting our loan–quarter panel data.[4] We show that firms switch from cash interest to PIK precisely when credit quality weakens, often after delinquency or loan valuation

[4]PIK-Notes embed deferral from the origination and offer no time-series variation; we therefore focus on ex-post PIK Toggles in the main tests.

declines. Toggling also concentrates late in a loan's life, consistent with short-term bridge financing ahead of a refinancing or workout. Loans that toggle are larger and typically involve dual equity+debt-holding lenders and PE-sponsored borrowers. Finally, PIK use is much more prevalent among borrowers without access to bank financing, indicating that toggles operate as a substitute for bank-provided liquidity in segments where access to revolving credit is limited. While banks specialize in providing credit lines, private credit lenders supply contractual flexibility through contractual features such as PIK. Overall, our results are consistent with the view that firms in distress are more likely to use the PIK Toggle option.

Our analysis of borrower and loan performance subsequent to PIK activation shows consistent results. We first document that PIK usage exhibits statistically significant and economically meaningful predictive power for credit deterioration in the quarters following the initiation of interest payment deferral. Using a variety of control variables and tight fixed effect specifications (based on borrower, industry, year-quarter, BDC, loan type, and seniority), we find that exercising the PIK option predicts 2-3 percentage point (pp) higher likelihood that a loan becomes delinquent (or "non-accrual") over the next quarter.[5] This is a sizeable increase given the unconditional likelihood that a loan becomes non-accrual of 3%. The quarterly fair value assessments of loans show that the fair value of loans (relative to the respective par value) declines following PIK usage. Finally, as loans with similar characteristics from the same borrower can be held in several BDC portfolios, we can study how valuation disagreement changes following PIK toggle use. Interestingly, we find that the fair value dispersion significantly increases after PIK activation, highlighting elevated uncertainty among private credit lenders regarding the fundamental value of the loans.[6]

[5]Lenders classify loans as non-accrual when interest payments by borrowers are at least 90 days overdue, which constitutes a "technical default". Importantly, the usage of the PIK Toggle option does *not* constitute a default event.

[6]We further employ a local-projection framework, which reveals that loan deterioration following PIK activation is persistent rather than transitory. Nonaccrual rates remain elevated, and loan values remain depressed for at least two years after PIK initiation. Cross-sectional tests corroborate these findings, demonstrating that loans utilizing PIK toggles exit the sample with significantly larger losses relative to comparable non-PIK loans.

To further distinguish between the efficient liquidity provision and zombie lending hypotheses, we examine heterogeneity in post-PIK outcomes across key loan and lender characteristics. We test whether PIK's effects vary by time to maturity (which would allow temporary distress to resolve), loan size (which might incentivize extend-and-pretend behavior on large exposures), dual debt-equity holdings (which reflect superior monitoring and shareholder-aligned interest), and pre-existing credit quality. The evidence contradicts the use of PIK as liquidity tool: loans that are already nonaccrual and use PIK experience continued deterioration, while maturity structure or loan size show no moderating effects. A notable exception emerges for private equity-sponsored borrowers, where PIK usage leads to significantly less deterioration, consistent with PE sponsors' willingness to inject additional equity in exchange for PIK terms or their superior restructuring expertise (Hotchkiss et al., 2021; Jang, 2024). Similarly, in some specifications, PIK-use by firms with equity holding lenders experience less credit deterioration. These cross-sectional patterns indicate that PIK activation does not selectively benefit borrowers facing temporary liquidity constraints, but rather extends financing to fundamentally distressed firms across most loan characteristics, with PE sponsorship—and dual-holding lenders—providing the only meaningful mitigating factor.

We further distinguish between PIK-Notes, where interest deferral is embedded at origination and subject to contemporaneous lender screening, and PIK-Toggles, where borrowers exercise the deferral option ex-post, typically when credit quality deteriorates. This distinction proves economically meaningful: loans using PIK-Toggles exhibit 19-26 percentage points higher probability to become nonaccrual compared to 4-11 percentage points for PIK-Notes, with similar patterns for exit losses (16-21 percentage points versus 0-4 percentage points). To rigorously test whether these differential outcomes merely reflect ex-ante borrower selection rather than information revelation from ex-post activation, we obtain novel firm-level data from martini.ai, an AI-powered credit intelligence platform that provides comprehensive credit ratings and financial metrics for middle-market private firms. Controlling for origination-date firm size and credit ratings, we confirm that ex-post PIK-toggle activation conveys distinctly negative information about deteriorating borrower prospects beyond what ex-ante screening captures, indicating that PIK-Toggles function primarily as forbearance mechanisms for fundamentally distressed borrowers rather than planned liquidity management tools.

Consistent with forbearance rather than efficient restructuring, PIK-toggle usage predicts a 27-30pp increase in subsequent maturity extensions but only a 8-11pp increase in debt-to-equity swaps, indicating lenders systematically delay loss recognition rather than implement formal workouts. This pattern of extending maturities while avoiding write-downs mirrors zombie lending and extend-and-pretend behavior documented, for example, in Acharya et al. (2022) and Crosignani and Prazad (2024), raising concerns about hidden credit losses accumulating in private credit markets.

Our evidence suggests that PIK is predominantly used by distressed firms rather than those facing temporary liquidity shocks, raising concerns that excessive PIK-based forbearance accumulates risks in BDC portfolios that could transmit to banks through increasing exposures to NBFIs (Acharya et al., 2024; Chernenko et al., 2025; Albertus and Denes, Forthcoming). While PIK deferrals do not require immediate cash outlays, they create liquidity pressures through a regulatory mismatch: deferred interest must be recognized as taxable income, compelling BDCs to distribute at least 90% as dividends to maintain RIC tax status despite receiving no corresponding cash inflows. We therefore examine whether excessive PIK provision leads BDCs to draw down bank credit lines, potentially transmitting credit risk to the banking sector.[7]

Despite substantial bank lending to BDCs, we find no evidence of risk transmission to banks through credit lines. BDCs with a high share of firms using PIK *reduce* bank debt relative to total debt (-0.51pp per 1pp increase in PIK usage) and credit line utilization (-0.38pp), reflecting covenant-based restrictions that effectively insulate banks from PIK-related losses. To document these covenant structures, we employ a web crawler to

[7]Also regulators and supervisors recognize the potentially important linkages between banks and private credit lenders: "[Private credit] lenders' reliance on banks for liquidity could pose systemic liquidity risk to the banking sector if a sufficient number of PC lenders (BDCs and other [private credit] funds) draw down on their bank credit lines simultaneously in response to adverse aggregate shocks", (Federal Reserve Bank of Boston, 2025).

systematically extract and classify PIK-related covenant terms from BDC credit agreements filed with the SEC. Interestingly, it reveals that almost all bank credit lines contain explicit restrictions on PIK collateral eligibility. These covenant-based constraints redirect the transmission channel: rather than flowing to banks, PIK-induced financing constraints manifest through reduced BDC asset growth and dividend payments, suggesting a contraction of private credit supply to particularly small and medium-sized firms.

Overall, PIK provisions function primarily as a contract-embedded forbearance mechanism rather than efficient bridge financing for temporarily distressed but viable firms. PIK usage follows idiosyncratic credit deterioration, predicts persistent non-accrual and fair value declines, and resolves through maturity extensions rather than balance-sheet restructuring – patterns that mirror extend-and-pretend behavior documented in bank lending but operating through contract design rather than capital constraints.

2 Related Literature

Our paper relates to different strands of the literature. First, our paper relates to a growing literature that highlights the increasing importance of private credit in corporate finance and BDCs as the largest group of lenders in the private credit market.[8] Many authors have studied the rise of nonbank direct lending and argued that an increase in bank regulation has been a major driving force behind this market shift (Davydiuk et al., 2024b; Irani et al., 2021). Others have analyzed BDCs' regulatory frictions and investment practices through the lens of agency conflicts (Kallenos and Nishiotis, 2020), competition with the broadly syndicated loan market (Hinzen et al., 2025), leverage limits (Balloch and Gonzalez-Uribe, 2021), market discipline (Davydiuk et al., 2024c), regulatory arbitrage (Chernenko et al., 2025), relationship lending (Jang, 2024), fund structure (Rintamäki, 2024), lenders' dual-holdings of equity and debt (Davydiuk et al., 2024a), PE-affiliations and contractual complexity (Jang et al., 2025; Robinson and Wallskog, 2025) and maturity

[8] Block et al. (2024) survey U.S. and European private debt investors and argue that BDCs are representative of typical private debt lenders in the U.S.

walls (Zawadowski and Albuquerque, 2025).Ours is the first paper to investigate contractual flexibility in private credit through PIK provisions and its implications for borrowers, banks, and private credit lenders.

Another strand of the literature underscores the important role of non-bank financial institutions (NBFIs) across various lending sectors, including mortgages (Buchak et al. (2018)), large corporate (Fleckenstein et al. (2025)), middle market (Chernenko et al. (2022)), and small business lending (Gopal and Schnabl (2022)). This expansion in NBFI market share is partly driven by bank financing, especially through committed credit lines and associated liquidity insurance. Acharya et al. (2024) document substantial funding relationships between unaffiliated banks and NBFIs via credit lines. Acharya et al. (2025a) highlight the risk of banks from lending to REITs via credit lines. Acharya et al. (2025b) document that banks respond to higher drawdown risk from firms financed by nonbanks by issuing fewer credit lines. Haque et al. (2024) argues that private debt serves as a substitute for long-term bank credit. Haque et al. (2025) highlight that bank lending to direct lenders is particularly attractive during monetary policy tightening. We contribute to this literature and show that, despite the reliance on bank credit lines, BDCs with a larger share of loans with deferred interest *decrease* their bank funding and utilization of credit lines, and how bank loan covenants in credit lines effectively mitigate bank exposure to private credit lenders.

A growing literature analyzes zombie lending and forbearance, a literature that is traditionally bank-based: weakly capitalized intermediaries evergreen credit to insolvent firms to postpone loss recognition, generating congestion and credit misallocation (Peek and Rosengren, 2005; Caballero et al., 2008; Giannetti and Simonov, 2013). Theory formalizes these incentives through limited liability and gamble-for-resurrection behavior (Bruche and Llobet, 2014), particularly of undercapitalized banks (Acharya et al., 2021).

We bring this lens to private credit. Using the universe of BDC loans and separating PIK-notes from discretionary PIK-toggles, we show that ex-post toggle exercise concentrates in distressed borrowers and predicts persistent nonaccrual and losses; resolution is primarily maturity extension, not balance-sheet restructuring. Our incremental contribution is to identify a contract-embedded forbearance mechanism outside banks and to trace its funding consequences: credit-line covenants largely exclude PIK collateral, insulating banks and shifting the adjustment to reduced bank funding and lower private credit supply.

Finally, our paper relates to the broader literature on leveraged loans and leveraged buyouts (LBOs), in particular. Kaplan and Stein (1993) document how public junk bonds replaced private bank loans for financing large LBOs during the 1980s buyout market. Demiroglu and James (2010) show the rising prevalence of deferred interest debt, with issuance increasing substantially around 2007. Guo et al. (2011) find that using deferred interest debt signals higher credit risk, with approximately 23% of LBOs from 1990–2006 featuring PIK structures. Both papers use an indicator for the existence of a PIK option at bond origination, but do not investigate when and whether firms actually exercise this option. We construct a novel dataset of firms that do (or do not) exercise the PIK option, their reasons, and the implications for firms, private credit lenders, and financial stability. To the best of our knowledge, we are the first who investigate PIK in the private debt market.

3 Data and Institutional Setting

To investigate the implications of deferring interest payments on firms and private debt lenders, we construct a dataset at the BDC and loan level using different data sources.

3.1 Data

Our main dataset is obtained from LSEG LPC's BDC Collateral. BDC Collateral contains the universe of BDCs from 2012Q1 onwards, including active as well as discontinued BDCs. It collects the information directly from the Securities and Exchange Commission (SEC) filings and augments the data, whenever feasible, with information from other LSEG products such as secondary loan market pricing. Importantly, it contains BDC balance-sheet data as well as the schedule of investments on a quarterly basis for private and public BDCs. BDC Collateral provides detailed loan-level information, including borrower names, industry, par amount borrowed from the BDC, interest rates (base rate, cash spread, and PIK spread), remaining loan maturity, loan seniority, and loan type. BDC Collateral groups loans into three loan seniority categories: first lien, second lien (both senior secured), and subordinated. They also provide additional information about security classes, which we group into five loan types: term loans, delay draw term loans (DDTLs), revolvers, unitranches, and others based on information provided in the security class column(s). BDC Collateral also provides quarterly performance measures, such as the fair value of the loan and the non-accrual status.

We augment BDC Collateral data with information from S&P Capital IQ and Pitchbook using Pitchbook identifiers and CIK numbers.[9] Pitchbook provides data both on the BDC level as well as for portfolio companies and investments. Pitchbook data lets us track whether the borrower is a private equity-backed backed at any given date and if a bank has also lent to it within the preceding five years.[10] Finally, we carefully remove any duplicates in the data and conservatively drop three (relatively small) BDCs from the sample whose business model has no resemblance to direct corporate lending.[11]

BDCs report their filings with the SEC on a quarterly basis. Our analyses at the BDC level are thus based on a BDC—quarter panel. BDCs are clearly identified using a CIK number. To track the same loan within a BDC over time, we aggregate the data at the BDC—Borrower—Seniority—Loan Type—Quarter level, and define our loan identifier accordingly.

Lastly, we obtain information about different firm credit quality, such as rating, and

[9]With matching, we use "Upload a list" functionality in the Pitchbook platform, which lets the user match firm names and other identifying information to corresponding Pitchbook identifiers using a sophisticated string-match algorithm. We augment the resulting automatic matches with manual matching.

[10]While Pitchbook deals do not capture all the bank loans issued in the U.S. middle market, the fact that we find that approximately 50% of the loans are associated with borrowers with past bank financing, which is a number that echoes findings of Haque et al. (2024) using confidential Fed Y-14 dataset, suggests that any incomplete information about bank reliance in our dataset is unlikely to be severe.

[11]We provide more details on data cleaning in the Online Appendix. Also, dropping the three funds has effectively no impact on any of the reported results.

firm size measures from MartiniAI, which is a financial analysis firm specializing in private markets. As this data is available only from 2017 onwards and is missing some firms, we use this data only to illustrate the robustness of the baseline results.[12]

3.2 Institutional setting and Empirical Facts

BDCs are closed-end investment funds that mainly lend to middle-market firms.[13] They are among the largest lenders in the non-bank direct lending market, with total assets of approximately USD 410 billion as of 2024 Q3 and total investments of USD 385 billion. In this section, we present several key institutional details and empirical facts related to PIK loans, and introduce the main datasets we use in the empirical section.

3.2.1 Evolution of PIK landscape

PIK usage share. To analyze trends in PIK adoption, we define the *PIK usage share* as the value-weighted proportion of loans in BDC's portfolio in which a loan pays PIK interest relative to all BDC's loans outstanding in a given quarter. More formally,

$$PIK\,usage\,share_{lt} = \frac{\sum_{b,k} Par_{blkt} \times PIK_{blkt}}{\sum_{b,k} Par_{blkt}} \tag{1}$$

where PIK_{bltk} is our key borrower-lender-loan-level indicator variable that equals one if borrower b pays some part of its interest obligation to lender l in quarter t for loan k, using PIK, and zero otherwise, and Par_{blkt} is the par value of a loan k at time t issued by borrower b to lender l. The summation is over all borrowers b and their loans k within a given lender's portfolio, Thus, $PIK\,usage\,share_{lt}$ is the value weighted fraction of the lender l's loan portfolio that is using PIK at time t.

Panel A of Figure 1 shows the *PIK usage share* for the full sample of loans over the 2012 to 2024 period and the average base rate over the same time period. We observe

[12] MartiniAI provides a mapping file that allows us to map a subset of firms to BDC Collateral identifiers. We allocate additional details of the variable construction to Online Appendix.

[13] National Center for the Middle Market defines the U.S. middle market as consisting of firms with annual revenues between $10 million and $1 billion (National Center for the Middle Market, 2024).

a cyclicality in PIK usage. During periods of economic expansion, PIK usage declined (from about 15% in 2014 to 10% in 2019), but we observe a significant increase first during the COVID-19 pandemic (during the 2020 to 2021 period) and an even larger PIK usage starting in 2022 when short-term interest rates increased in the U.S. due to tighter monetary policy. As loans in the private debt market are largely floating-rate, a sudden and substantial interest rate hike increased liquidity pressure on these borrowers.

Panel B of Figure 1 complements this picture by showing PIK usage share with the average nonaccrual rate in the sample and share of loans that are valued below 80% at any given quarter. The most notable peaks in these distress series occurred in 2016, following the oil-price shock, and in 2020, following the COVID-19 shock. Interestingly, following the oil shock, there does not occur a corresponding increase in PIK usage share at all, while in the case of the COVID-19 shock, the PIK usage does lag the distress series, but also stays elevated until 2021Q1, whereas the distress series declines very rapidly following the initial shock that occurred in March 2020.

Average PIK spread. How much interest payments are PIK'd varies across PIK loans, but on average, it has been substantial, about 5 percent of the loan balance per annum. Panel A in Figure 2 presents the quarterly average PIK spread from 2012 to 2024 among loans that actively PIK some part of the interest. We observe a distinct increase in PIK spread starting from 3.6% in 2013 and peaking at 5.5% in 2018, after declining back down to below 5% in 2021. After that spread has remained stable throughout the subsequent period of rising interest rates.

Another way to visualize PIK activity is to look at the average share of total interest paid using PIK across all loans (including those that do not use PIK). Panel B in Figure 2 shows the average ratio between PIK spread and all-in-yield, which we call PIK spread share. The figure illustrates this for both equal-weighted and par-value weighted averages. The higher level of PIK spread share for the value-weighted average relative to the equal-weighted average suggests that PIK is used more among bigger loans. The figure illustrates how PIK spread share increased substantially during COVID-19, up to 10.5%, suggesting that, on average, about 10 cents of every interest paid at this time was capitalized in loan balances. However, recently this spread share has declined, mainly due to an increase in base rates, which mechanically increases the denominator of the PIK spread share without having a similar direct impact on the numerator.

Heterogeneity in PIK use. The patterns shown above, however, mask considerable heterogeneity. Figure 3 illustrates some of the most salient dimensions of heterogeneity in PIK usage. First, Panel A focuses on PIK usage share by security type, where loans are categorized as either *Senior* (first and second lien) or *Junior* (subordinated debt). The figure illustrates that junior debt exhibits higher PIK usage overall. However, the PIK usage share in senior loans exhibits a similar pattern of spiking in times of liquidity needs, such as following COVID-19 and the monetary tightening that started in 2022.[14]

Second, in Panel B, we illustrate that a big fraction of the PIK usage is mainly done by borrowers who have not received bank financing within the preceding five years. We observe that PIK usage is significantly more prevalent among these "unbanked" borrowers, suggesting that PIK serves as an alternative liquidity management strategy for firms that cannot rely on bank financing.

Third, in Panel C of Figure 3, we focus on the dimension of heterogeneity that relates to *how* PIK is used by borrowers. PIK is utilized in private debt contracts in two primary ways: Borrowers may defer interest payments from the outset of loan origination and do so throughout the loan's lifetime, or borrowers may have the option to initially pay cash interest but later switch to deferred interest payments if deemed useful. The former arrangement is typically termed "PIK Note", while the latter is referred to as a "PIK Toggle." Correspondingly, we identify a loan as a "PIK Note" if it pays PIK interest at every period during its lifetime.[15] Panel C of Figure 3 plots the PIK usage share for each type of PIK loan, while excluding the other type of PIK loans from the calculation.[16] The

[14]The reason why Panel A in Figure 1 exhibits a declining trend in PIK usage from 2012 until 2019, while the series in Panel A of Figure 3 does not, is because there has been a shift in BDC's portfolio composition, from relatively PIK-heavy junior debt toward more PIK-light senior debt.

[15]Another way to define these is to call loans that had PIK at origination (but not necessarily all the time) as PIK notes, and those without PIK at origination (but have later) as PIK toggles. This alternative definition overlaps closely with our baseline definition, and we show in the Online Appendix that our results are qualitatively similar when using it.

[16]The fact that we exclude the PIK notes when calculating PIK toggle usage share (and vice versa) is

figure illustrates that over the past decade, PIK-toggle loans, in which borrowers choose to use their PIK option only when necessary, have become increasingly prominent in private credit markets. The trend seen in PIK usage share reflects the overall market shift toward PIK toggles, and it is also related to the shift in BDCs' portfolio composition from junior debt to senior debt, as PIK-notes are more likely to be subordinated debt. Next, we will delve into these differences in more detail.

3.3 Summary statistics

Our empirical exercises are conducted using three datasets, in the following order: First, we utilize a loan-level panel dataset. Second, we use a loan-origination-level cross-sectional data, which we obtain after collapsing the panel data based on each loan's first observation dates. Third, we use BDC-level panel data. We present these datasets by first focusing on key summary statistics for the two panel datasets and then exploring heterogeneity in characteristics and outcomes between PIK-notes, PIK-toggles, and non-PIK'd loans using the cross-sectional data. Panels A and B in Table 1 present summary statistics at the BDC-level (Panel A) and loan level (Panel B) over the 2012Q1 to 2024Q4 period.[17]

The average BDC in our sample has a PIK usage share of 13%, with considerable variation across funds (standard deviation of 16%). Mean assets under management (AUM) per BDC are USD 1.62 billion, although the distribution is skewed, with a median asset size of USD 0.59 billion. BDCs hold, on average, investments in 86 portfolio companies and have an average leverage ratio of 0.4. The median fund age is 6 years, but several BDCs have significantly longer operating histories. The median return on equity (ROE) among BDCs is 9%. Banks provide substantial funding, representing a median share of 45% of BDCs' total debt. Additionally, BDCs actively utilize credit lines, with an average utilization rate of 54%.

At the loan level, PIK is used in 10% of observations. The average all-in yield is

the reason why the level of both PIK usage share for both loan types is frequently below the level of total PIK usage share plotted in Figure 1.

[17] All variables are defined in detail in the Appendix in Table A.

9.56%, with higher-risk loans having average PIK spreads of around 4.96%, compared to average cash spreads of 6.49%. Most loans feature floating rates, averaging a base rate of 2.96%, although this varies significantly over time. The average loan size is approximately USD16 million, and loans typically trade at a fair-to-par ratio of 0.95, indicating moderate discounts that widen notably during downturns. The median remaining maturity is 51 months (about 4 years). Approximately 19% of observations involve lenders simultaneously holding equity and debt stakes in the borrowing firm. Furthermore, 14% of the sample observations are identified as PIK toggles, while 4% are PIK notes.[18] 84% of loans are first-lien senior secured, 11% are second-lien, and 5% are subordinated, reflecting BDCs' preference for secured lending.

Panel C of Table 1 takes a snapshot of loan features at origination date, where we refer to origination date as the year-quarter when the loan first enters the sample. We also employ several filters to drop loans that may contain some measurement error about the exact origination timing, which we describe in detail in the Online Appendix and in the notes of Table 1. PIK-Toggle and PIK-Notes serve fundamentally different purposes. PIK-Toggle are more common, senior-secured instruments (85.8% first lien) used as optional liquidity insurance, deployed only 41.6% of their lifetime on average. PIK-Notes, in contrast, are permanent capital structure features (100% deployment) deployed by growth-focused borrowers committed to systematic profit reinvestment, featuring compressed cash spreads, higher PIK yield components (37.4% versus 16.1%), and often unsecured or subordinated positioning (48.9% unsecured).

Different lender practices might explain these structural differences. PIK-Toggle lenders rely on collateral and seniority for protection, accepting floating rates and tolerating frequent extensions (57.2%). PIK-Note lenders employ intensive monitoring and covenant discipline, preferring fixed rates to mitigate borrower rate uncertainty in volatile growth environments. The 300 basis point all-in-yield premium on PIK-Notes likely reflects compensation for subordination and monitoring burden.

[18] In practice, the proportion of PIK toggles is a lower bound, as loans with unused PIK options remain unobserved by econometricians.

3.4 Example of PIK reporting

Table 2 illustrates deferred interest (payment-in-kind, PIK) using a concrete loan-level example: a First Lien Senior Secured Term Loan to Dynamic Energy Services International as reported by PhenixFIN, a BDC and formerly known as Medley Capital Corporation. The table decomposes the stated all-in yield into a base rate (reported alongside an effective base, consistent with a contractual floor), a cash spread, and a PIK spread, and then links these pricing terms to the loan's reported par value, fair value relative to par, non-accrual status, and remaining months-to-maturity.

In the early part of the sample (2014Q1–2016Q1), the disclosures indicate a purely cash-pay structure: the cash spread is consistently 8.5% while the PIK spread is 0%, and the binary PIK indicator, which we construct, remains 0. Over this same window, the reported par generally drifts downward (from 19.0 to 17.1), consistent with amortization or principal paydowns, and Fair/Par stays close to 1, indicating valuations near par.

Starting in 2016Q2, the reporting first shows deferred interest: the PIK spread turns positive at 1.5% (with the cash spread still 8.5%), which raises the all-in yield from 9.5% to 11% and flips the PIK indicator to 1. Shortly thereafter, in 2016Q4, the loan's interest composition shifts dramatically toward full deferral: the cash spread drops to 0% while the PIK spread jumps to 13.5%. From that point onward, the loan's all-in yield remains very high (roughly 14–16%) and varies primarily with movements in the base rate rather than with any cash-pay component.

Crucially, following the move to substantial (and then effectively exclusive) PIK interest, the reported par value begins to rise over time (e.g., from 16.5 in 2016Q4 to 21.8 by 2018Q4), consistent with PIK interest being capitalized into principal instead of being paid in cash. At the same time, the table shows a sharp deterioration in credit quality: Fair/Par falls markedly, and the loan is marked non-accrual beginning in 2018Q1, after which the fair value declines toward (and ultimately essentially to) zero even though the contractual terms continue to list a large PIK spread.[19]

[19] The series also contains discrete jumps in reported par and months-to-maturity (e.g., 2015Q4 and 2019Q1), consistent with amendments and refinancing that reset reported terms. These shifts do not alter

Overall, Table 2 demonstrates how a positive PIK spread in BDC portfolio disclosures can be used to identify the presence of deferred interest, and how the combination of high PIK spreads with rising par (despite falling fair value and non-accrual status) is indicative of PIK interest accruing mechanically to principal even as the underlying credit performance deteriorates.

4 Why do firms use the PIK option?

We begin our analysis by examining the determinants of exercising the PIK option, estimating a regression model via OLS where we introduce several variables that categorized into four groups called *Distress*, *Loan Terms*, *Ownership*, *Lending Relationship*. We track each variable within a group with a superscript j. The model we run is the following:

$$\begin{aligned} PIK_{blkt} = &\sum_j \beta_{1j}\, Distress^j_{blkt} + \sum_j \beta_{2j}\, Loan\,Terms^j_{blkt} + \sum_j \beta_{3j}\, Ownership^j_{blt} \\ &+ \sum_j \beta_{4j}\, LendingRelationship^j_{bt} + Fixed\,Effects + e_{blkt} \end{aligned} \tag{2}$$

The *Distress* variables include: $NonAccrual_{blkt}$, which is an indicator variable that takes a value of one if the loan k from lender l to borrower b is marked as nonaccrual at quarter t, and zero otherwise, $I(Fair/Par_{blkt} < 0.8)$ which takes a value of one if the loan k is valued at below 80% at time t, and zero otherwise.

The *Loan Terms* variables include: *Ln(Loan size)*, *Effective base rate* (a maximum of the current base rate and the interest rate floor), *Fixed-rate loan* -indicator, the loan's *All-in-spread* at the time of the origination.[20] Loan seniority and loan type indicators are controlled with corresponding fixed effects.

The *Ownership* variables include: $Dual\,holding_{blt}$ is an indicator variable that takes

the central pattern: the onset and persistence of a positive PIK spread coincides with periods in which par increases in a way consistent with deferred interest being added to principal.

[20]We control for the all-in-spread at origination date τ rather than at date t since using PIK often mechanically increases the all-in-spread, as there is often a some type of drawdown fee. This makes the two variables highly co-linear, and running *All-in-spread* a bad control.

a value of one if the lender l also holds an equity stake in the borrowing firm b at time t, while $PE\,Sponsored_{bt}$ is an indicator if the borrower is PE-backed.

The *Lending Relationship* variables include: $Ln(Number\,of\,BDCs)$ that lend to that borrower b in time t. $Bank\,financing_{bt}$ is an indicator variable that takes a value of one if the borrower b has received bank financing within the preceding five years from t.

We include only loans with PIK toggles and loans without observable PIK components in the sample, explicitly excluding all PIK notes. We impose this restriction because our primary interest is the borrower's active decision to exercise the PIK toggle after loan origination.[21] We cluster the standard errors at the $Borrower$, BDC, and $YearQtr$ levels. Our sample period for all loan-level tests is 2012Q1-2024Q1, with the end date determined by a loss of data coverage for some variables.

Table 3 presents the regression results. We find evidence that each of these categories has some influence on PIK use. First, across all specifications, we find that borrowers are more likely to defer loan interest payments if loans are classified as non-accrual or are valued at a significant discount. This suggests that borrowers who experience distress or reduced cash flow capacity often resort to PIK interest. Second, some loan terms are strongly associated with PIK use. Larger loan balances are more likely to increase PIK use; similarly, PIK use itself increases loan balances with the capitalized interest. Loans with shorter maturity are also more likely to be PIK'd, and we find a strong, persistent association with PIK use and fixed interest rate. This is because, although most of these loans are tied to a floating rate, like LIBOR (later SOFR), at origination, firms often temporarily shift to fixed interest payments when using PIK. Third, ownership structure also seemingly plays a role. We find that PIK loans are typically associated with the lender having some equity-like stake in the borrowing firm (i.e. *Dual-holding*), and PE-sponsored firms are more likely to use PIK. Fourth, we find that firms that have not received a bank loan in the preceding five-year period are much more likely to use PIK, indicating that firms that lack outside financing options are most likely to benefit from PIK use.

[21] Including the PIK notes has little impact on the results, although there also exists some important heterogeneity, which we analyze below.

The different fixed effects also reveal interesting facts about PIK use. For example, when we move from Column (3) to Column (4) by adding $Industry \times YearQtr$ fixed effects, we see that the Adjusted R^2 increases only by 1%. This is interesting because it reveals something about the nature of the shocks that trigger firms to use PIK provisions. Under the liquidity provision view, the users of liquidity typically face temporary cash flow shocks but do not face permanent economic distress. So, under this view, it can also be a value-enhancing for lenders to offer liquidity when borrowers face temporary industry-wide shocks, as this type of distress is not a result of poor economic performance relative to peers, but rather an adverse consequence of a macroeconomic shock. A case in point is the service industry that faced temporary liquidity problems due to the COVID-19 lockdown restrictions. As lockdowns had heterogeneous impact across industries but more homogeneous impact within industries, and this shock was expected to be temporary to the extent lockdowns were expected to be temporary, then PIK could be a good response for these temporary industry-wide shocks. However, the low incremental R^2 suggests that most PIK use is instead driven by idiosyncratic, within-industry, firm-specific factors rather than industry-wide shocks.

Another piece of evidence that speaks in favor of the forbearance view is the relatively large increase of 4 pp in Adjusted R^2 when we move from Column (6) to Column (7) and replace $Borrower + BDC$ with $Borrower \times BDC$ fixed effects. The 4 pp increase suggests that time-invariant, relationship-specific factors between the lender and borrower explain a significant portion of the total variation in PIK use. These relationship-specific factors should matter less under the efficient liquidity provision view; however, they are often viewed as a significant determinant of zombie lending (Hu and Varas, 2021). In the next section, we corroborate these facts by showing that the distress associated with PIK use is also more likely to be permanent than temporary.

5 Implications of PIK Usage for Loan Performance

5.1 Panel tests: PIK and future loan outcomes

In the previous section, we learned that distressed firms and firms with lack of access to bank financing are typical users of PIK. This suggests PIK may be useful for the borrower by providing some immediate relief. If this view is shared by the lender, we would expect the loan value to increase following PIK use and the likelihood of nonaccrual status to decrease. In this section, we test this by studying what happens to the loan following the borrower's decision to defer cash interest payment. We run the following OLS regression model

$$y_{blk,t+1} = \beta_1\, PIK_{blkt} + Controls + Fixed\,Effects + e_{blkt} \tag{3}$$

where the dependent variable $y_{blk,t+1}$ takes three forms. First, $NonAccrual_{blk,t+1}$ is an indicator variable that equals one if the loan is classified as non-accrual in *t+1*. Second, $Fair/Par_{blk,t+1}$ is the loan value measured as $Fair/Par$-ratio at *t+1*. Third, $CSD(Fair/Par)_{bk,t+1}$ is the cross-sectional standard deviation of similar loans' $Fair/Par$-ratio across all BDC's portfolios at the end of period $t+1$. Thus, it is a measure of valuation disagreement among different lenders regarding the loan.[22]

The motivation for the first two variables is that using PIK contains valuable information and may signal future distress that is not incorporated in the current price. The motivation for the third variable is that a loan is frequently held by different BDCs that have their own fair value assessment. Since using PIK may increase both default risk and agency costs of debt, this might make it more difficult for lenders to assess the fair value of a loan.[23]

[22]For example, two loans held by two different lenders at the same period are considered similar if they are issued by the same borrower, have the same seniority (e.g. both are first lien senior secured), and have the same loan type (e.g both are term loans).

[23]This view is shared by many BDCs themselves. For example, Kennedy Lewis Capital Corp writes in their 2024 annual report: "*[...]PIK instruments may have unreliable valuations because the accruals require judgments about collectability of the deferred payments and the value of any associated collateral*".

In each specification, we also include the current time t value of the dependent variable, as these series are highly autocorrelated, and we want to test if PIK contains information that is not already captured in these variables. We employ a stringent set of model specifications that incorporate all control variables shown to have explanatory power for PIK usage (compare Table 3), as well as fixed effect combinations for borrower, industry, year-quarter, BDC, loan seniority, and loan type. $Industry \times YearQtr$ fixed effects capture any time-varying differences between industries and thus ensure that the association is not simply driven by the fact that firms in specific industries that are more likely to use PIK, subsequently underperform. This also relates to our discussion about these fixed effects in the previous section. Borrower fixed effects address persistent time-invariant differences between borrowers that allow us to control for factors such as firm management, corporate culture, and firm size (at least approximately). If some BDC characteristics correlate with BDC's PIK provision activity, then this creates a concern that these same characteristics might systematically influence lenders' valuation practices or risk-taking tendencies. Thus, including $BDC \times YearQtr$ fixed effects accounts for these time-varying observable and unobservable characteristics, such as risk appetite, lending strategy, and funding costs, and ensures that these supply-side factors do not explain the results. $BDC \times Borrower$ fixed effects control for endogenous matching between lenders and borrowers. Finally, *LoanType* and *Seniority* control for differences in default risk between different types of loans. We use three-way clustering of the standard errors by *Borrower*, *BDC*, and $YearQtr$.

In Columns (1)-(2), the positive and strongly statistically significant coefficient on PIK suggests that when the firm exercises the PIK toggle for the loan in period t it predicts a heightened probability that the loan will be assigned as nonaccrual in the next period $t + 1$, even above what we can infer from the time t nonaccrual status of the loan. Similarly, Columns (3)-(4) show a similar story when we use $Fair/Par$ at $t + 1$ as the dependent variable. Columns (3) and (4) indicate that a single-period use of PIK is followed by 100bps decline in valuation in the next period. The fact that we control for period t loan value, which is reported while knowing that PIK has been used in that same period t suggests that not all negative information about PIK use is incorporated in the loan prices in a timely manner. Extrapolating from these local linear estimates, we can conclude that a more persistent use of PIK—by for example, 10 quarters—is associated with a 10 pp cumulative decline in loan value.

These results suggest that PIK use is generally not followed by reversal in a firm's financial situation but instead is actually followed by statistically significantly worse outcomes for the loan relative to an observably similar loan that does not use PIK. This indicates that lenders, or the third-party analysts who are valuing the loans, do not see PIK as a remedy to the borrower's economic problems, and the firm's need to use PIK typically is a signal that current loan value is too optimistic since default risk is likely to increase.

Lastly, in Columns (5)-(6), we focus on valuation dispersion. The results show that PIK use is generally followed by higher valuation dispersion among the lenders. This indicates that PIK also adds uncertainty about different future paths, with some analysts viewing PIK use as a more positive or negative signal than others.

5.1.1 Impulse response functions

To evaluate the persistence of the predictive power of PIK for $NonAccrual$, $Fair/Par$ and $CSD(Fair/Par)$. We run the following local-projection regressions

$$y_{blk,t+h} = \beta_h PIK_{blkt} + \sum_{j=0}^{4} \gamma_{hj}\, y_{blk,t-j} + Controls + FixedEffects + e_{blk,t+h}$$

where h runs from 1 to 8 and $y_{blk,t+h}$ is either $NonAccrual$, $Fair/Par$ or $CSD(Fair/Par)$ at time $t+h$ for loan k of borrower b held by lender l. PIK_{blkt} is an indicator variable that equals one if the PIK toggle is used for loan k in time t. We include the following fixed effects: $YearQtr \times Industry + YearQtr \times BDC + Borrower \times BDC + Seniority + LoanType$. In addition to the five lagged dependent variables, we include the following controls $Ln(Loan\,Size)$ $Effective\,Base\,rate$, $Fixed\,rate\,loan$, $Ln(Time\text{-}to\text{-}Maturity)$, $Dual\,holding$, $PE\,Sponsored$, $Bank\,financing$ with all measured at time t

and *All-in-spread* measured at the origination date τ. Then we collect the β_h coefficients and plot them in a graph with the 95% confidence based on three-way clustered standard errors by $Borrower$, BDC, and $YearQtr$.

Figure 4 shows that the persistence of predictive results for $NonAccrual$, $Fair/Par$, and $CSD(Fair/Par)$ extends beyond just over the next quarter. The predictive power of PIK usage persists even after 2 years for $NonAccrual$ and $Fair/Par$. These results corroborate the view that users of PIK are generally experiencing persistent difficulties rather than temporary problems, and PIK use is generally followed by further distress rather than a swift recovery. With $CSD(Fair/Par)$, the effect is a bit more short-lived as the β_h coefficient converges back to zero between quarter $h = 5$ and $h = 6$. This means that valuation disagreement between lenders following PIK use seems to fully self-correct over time, probably because these valuations are public information and lenders may learn from each other's valuations.

5.1.2 Heterogeneity

Next, we investigate whether the use of PIK toggle as a signal of a firm's repayment prospect masks heterogeneity between borrowers. To do so, we run the following OLS regression

$$\begin{aligned} y_{blk,t+1} = {} & \beta_1 \, PIK_{blkt} + \beta_2 \, y_{blkt} + \beta_3 \, X_{blkt} + \beta_4 \, PIK_{blkt} \times y_{blkt} \; + \beta_5 \, PIK_{blkt} \times X_{blkt} \\ & + Controls + Fixed\,Effects + e_{blk,t+1} \end{aligned} \tag{4}$$

We now add the interaction terms between PIK and lagged dependent variable y_{blkt} as well as several other characteristics—first just with PE sponsored indicator, but then also with log time to maturity, dual holding indicator, log loan size—all stacked in vector X_{blkt}. We also include other similar controls that were used above. As our focus is primarily on the interaction terms, when analyzing the results, we restrict our attention to estimates for β_1, β_4, and β_5.

Table 5 presents the results. Let us first focus on Columns (1)-(3) that show the results for $NonAccrual$. In Column (1), we include only the $PIK \times PE\,Sponsored$ interaction, loan controls that we also used in Table 3 and $YearQtr$, $Borrower$, $LoanType$, $Seniority$ fixed effects. Interestingly, the positive sign for PIK and the negative sign for $PIK \times PE\,Sponsored$, but smaller in absolute terms, suggest that the negative signal of PIK gets dampened when the borrower has a PE sponsor. This suggests that PE sponsored firms are special as they are able to avoid delinquency with better success when using PIK compared to non-PE sponsored firms. We also study other sources of heterogeneity in Column (2). While $PIK \times PE\,Sponsored$ remains economically and statistically significant in these Columns, most other interaction terms are zero. There are exceptions, though. PIK use by firms with equity-holding lenders tends to experience less credit deterioration, which could indicate that only more comprehensive workouts involving debt-to-equity swaps can make PIK a viable form of support. Similarly, in Column (2), the positive coefficient PIK (while controlling for $PIK \times NonAccrual$) indicates that even if the loan is not nonaccrual this period, using PIK indicates that the chances grow that it will be nonaccrual the next period. Moreover, the positive coefficient on the interaction $PIK \times NonAccrual$ indicates that if a loan is nonaccrual *and* uses PIK, there are higher chances that it will continue to be assigned as nonaccrual in the next period relative to the case when it is nonaccrual but does not rely on PIK. However, in Column (3) when we add $YearQtr \times BDC$, $BDC \times Borrower$, and $YearQtr \times Borrower$ fixed effects—the last, which automatically restricts the sample to firms that have multiple loans outstanding—we find that only the PIK variable and $PIK \times PE\,Sponsored$ interaction term remain statistically significant. This suggests that PIK is likely to lead to higher delinquencies for the loans that are tied to PIK interest, even when conditioning on the borrower's overall financial situation with $Borrower \times YearQtr$ fixed effects. Thus, PIK can be a bad signal not just about the borrower's overall prospects but also about the prospects of the very loan that uses PIK. Similarly, the presence of a PE sponsor helps to prevent future loan delinquencies for these very same loans, suggesting that asymmetric loan outcomes for PIK users are less likely to occur when a PE sponsor is involved.

We find similar results when we use the $Fair/Par$ as the dependent variable in Columns (4)-(6). First, the coefficient for the interaction term $Fair/Par \times PIK$ suggests that the starting value of $Fair/Par$ also matters to the loan response following PIK use. For example, the estimates in Column (2) suggest that when the loan is valued at 80 cents on the dollar and loan uses PIK, then the expected next period fair/par ratio is ($-0.09 + 0.09 \times 0.8 = -0.018$) 78.2 cents on the dollar, while if the starting point is that loan is valued on par, then the expected decline in loan value is zero ($-0.09+0.09\times1 = 0$). Said differently, the negative signal of the PIK gets amplified if the existing value of the loan is low. Second, similarly, as we saw with $NonAccrual$, we observe that in Columns (4)-(5), PE-backing of the firm has a positive impact on PIK users, and PE-backed firms do not expect as big declines in loan values following PIK use. In column (6), this effect is no longer statistically significant, potentially because the $YearQtr \times Borrower$ fixed effects restrict the variation within the same firms with multiple loans. However, the nonlinear effect of $Fair/Par \times PIK$ on future valuations remains.

To check visually if these results for PE-sponsored borrowers make sense, we plot in Figure 5 the average value of the loan (on the left) and non-accrual probability (on the right) 3 years before and after the first time PIK toggle is used. What the figure clearly illustrates is that deterioration of credit conditions, measured by declining average loan value and increasing non-accrual rate, starts typically already slightly before the PIK is first used, suggesting that PIK is more likely to be a symptom rather than a cause of a firm's difficulties. However, based on the visual inspection, it looks like using PIK also does little to help this deteriorating trend since credit continues to deteriorate following the first time PIK is used, all the way until the end of the observation window.

Interestingly, however, the different lines for PE-sponsored and non-sponsored firms suggest that there exists some heterogeneity in these trends. After the introduction of PIK, the sharp decline in loan value seems to moderate slightly for PE-sponsored firms, while similar moderation is not observable among the loans of non-PE-sponsored firms. This widening gap can also be observed in the average non-accrual rate on the right side of the figure, though the "kink" among PE-sponsored loans is less distinct. These patterns are thus consistent with the documented results in Table 5.

5.2 Cross-sectional test: PIK and future loan outcomes

5.2.1 Heterogeneity from PE sponsorship

The panel tests above are useful to understand the short-term dynamics around PIK use, but they do not reveal what the definite outcomes are for loans that end up using PIK and how these outcomes compare against loans that do not defer interest payments. Similarly, based on the previous test, we cannot determine whether PE-sponsored ownership helps permanently prevent worse loan outcomes or is simply a short-term effect.

Thus, we now focus on cross-sectional data, using initial loan characteristics at loan origination, and examine how these characteristics explain the likelihood that a loan will later become nonaccrual and exit the sample with a significant discount at the termination date. As explained in more detail in Section 3, we define origination quarter as the year-quarter of the first observation when the loan appears in the sample.

Precisely, we start with the following cross-sectional regression

$$y_{blk,\tau} = \beta_1\, PIK\, Toggle_{blk,\tau+n} + Controls + Fixed\, Effects + e_{blk,\tau} \tag{5}$$

where τ denotes the year-quarter when the loan first appears in the sample, which we call the origination period and the loan outcome, $y_{blk,\tau}$, is either $Future\, NonAccrual_{blk,\tau+m}$, which takes a value of one if the loan becomes nonaccrual at any date $\tau+m$ after origination date τ, or $I(Fair/Par_{blk,T} < 0.8)$, which takes a value of one if the loan has a valuation below 0.8 at the loan termination quarter T. The main explanatory variable of interest, $PIK\, Toggle_{blk,\tau+n}$, takes a value of one if the borrower uses the PIK option at some date $\tau + n \geq \tau$ following loan origination. Although we studied PIK toggles above in previous sections, we use this more explicit reference $PIK\, Toggle_{blk,\tau+n}$ to separate this cross-sectional variable from the panel data variable PIK_{blkt} used above, and because we introduce comparative results between PIK notes and PIK toggles further below in this section. We also include a set of control variables that capture the observable loan terms and borrower characteristics (same as used above) measured at the time of origination and $Pre\text{-}PIK\ Amend_{blk,\tau+s}$, which we define below. We also standardize the continuous variables (but not the binary variables) to ease the interpretation of some of the results.

In addition to the baseline model, we are also interested in studying the heterogeneity in these outcomes, we augment this baseline specification by adding an interaction term $PIK\,Toggle_{blk,\tau+n} \times PE\,Sponsored_{b,\tau}$ and interaction terms with $PIK\,Toggle_{blk,\tau+n}$ and several other origination dated characteristics. These characteristics relate to loan terms, such as loan size, maturity, and dual-holding, similarly to the previous section, but we also include $Pre\text{-}PIK\ Amend_{blk,\tau+s}$, a variable which takes a value of one if the loan has experienced an amendment before the first time PIK is used for that loan.[24] While we cannot observe amendments directly, we use instances of maturity extension or a loan becoming non-accrual as proxies of an amendment occurring. This is because becoming non-accrual automatically triggers a renegotiation or an amendment, while a maturity extension also requires an amendment. With $I(Fair/Par_{blk,T} < 0.8)$ as the dependent variable, the sample is further restricted to loans that have already exited the sample since we need this to observe each loan's termination date T. Table 6 shows the results.

Columns (1) and (2) indicate that firms using the PIK option are 22-23pp more likely to experience delinquency at some point in the future compared to those loans that do not use the PIK option. Focusing then on Column (3), we observe a large and positive coefficient for $PIK\,Toggle_{blk,\tau+n}$ and a large negative coefficient on the interaction term $PIK\,Toggle_{blk,\tau+n} \times PE\,Sponsored_{b\tau}$, which suggests that using PIK toggle is followed by an elevated nonaccrual probability, but more so for non-PE-sponsored firms. This is consistent with the hypothesis that lenders typically require PE sponsors to inject additional equity in exchange for debt amendments that increase debt burden, such as PIKs. With non-sponsored firms, there may not exist similar deep-pocketed financial backers that can do this, which then leads to a higher delinquency probability.[25]

[24] In other words, we require that $\tau + s \leq \tau + n$ and if there is no PIK used at all, but there is an amendment, then this is automatically satisfied.

[25] While we do not observe in our data these PE sponsors' equity injections, prior studies suggest that

Interestingly the interaction term $PIK\,Toggle_{blk,\tau+n} \times Dual\,holding_{b\tau}$ is positive and not statistically different from zero, contrasting the result shown in Table 5 where *Dual holding* is measured at time t and not at origination τ. These contrasting findings may indicate that the mitigating effect which is presented above in the panel data tests seems to arise from dual-holding measured at the time of PIK use, which can arise e.g., following a post-origination workout and debt-to-equity swap, but not from at-origination-equity-stakes.

Another important finding is that the interaction term $PIK\,Toggle_{blk,\tau+n} \times Pre\text{-}PIK\,Amend_{blk,\tau+s}$ is positive and statistically significantly different from zero, suggesting that PIK toggles that are activated after a loan amendment, rather than before them are associated with a higher probability of experiencing nonaccrual compared to amended loans that do not use PIK afterwards.

Columns (4)-(6) complement these results by instead looking at the outcome that the loan exits the sample with a significant discount. The results are analogous: First, using PIK toggle post-origination is followed by a 22-26 pp higher probability that the loan will also exit the sample with a significant discount—a finding which is also statistically significantly different from zero at 1% critical level. Second, these adverse outcomes seem to be only slightly mitigated by the presence of a PE sponsor for the borrowing firm. In contrast to nonaccrual results, the coefficient for the interaction term $PIK\,Toggle_{blk,\tau+n} \times Pre\text{-}PIK\,Amend_{blk,\tau+s}$ is still positive but not statistically significant.

5.2.2 Heterogeneity between PIK-Notes and PIK-Toggles

Next, we draw attention to the heterogeneity in loan outcomes between PIK-Notes and PIK-Toggles. As described earlier, firms might use PIK in two different ways, either as a permanent component of interest payment right from the loan origination ("PIK-Note") or switch to PIK at some point before loan maturity ("PIK-Toggle"). In the previous section, we have focused on PIK-Toggles as they are more similar to contingent liquidity provision

they are frequently used in distress situations. For example, Hotchkiss et al. (2021) finds that PE owners are more likely to inject new equity into firms in distress situations, while Jang (2024) finds similar evidence from the COVID period and also shows that equity injection clauses are regularly included in the contracts between private debt lenders and private equity sponsors.

through bank credit lines, whereas PIK-Notes are similar to bonds (often subordinated and fixed-rate), and are often designed as a permanent way for borrowers to save cash to finance a strategy of aggressive growth.

A crucial difference between PIK-Notes and PIK-Toggles lies in the timing and informational environment of their use. PIK components in PIK-Notes are exclusively put in place at origination, when lenders can evaluate the borrower's contemporaneous creditworthiness and calibrate loan terms to the observed risk profile. This aligns with recent evidence that private debt funds rely heavily on ex ante screening and sponsor relationships to manage credit risk (Block et al., 2024; Jang, 2024). In contrast, PIK-Toggles are exercised ex-post, typically when borrower quality deteriorates or refinancing options become prohibitively costly.[26] As PIK-Notes are extended under conditions of active risk assessment, we hypothesize that such borrowers are less likely to enter distress. By contrast, toggling into PIK reflects deteriorating fundamentals and is more likely to precede severe loan outcomes

To test this, we construct two variables: $PIK - Note_{blk}$ takes the value of one if a lender has issued a PIK-Note to a borrower at origination (but the borrower has not toggled afterwards); $PIK - Toggle_{blk}$ takes the value of one if the borrower has activated the PIK-Toggle at some point before loan maturity (but did not have a PIK-Note). We estimate equation (3) using OLS cross-sectional regression, while using $Future\,NonAccrual_{blk,\tau+m}$ and $I(Fair/Par_{blk,T} < 0.8)$ as the dependent variables. We include all standard control variables measured at origination using OLS and, as before, restrict the sample period to loan originations that occur between 2012Q2-2021Q4.

Table 7 documents results consistent with this hypothesis. In Panel A, where we focus on the full sample, the point estimate in Column (1)-(3) suggests that firms that use PIK-Toggle have a 19-26pp higher likelihood that a loan becomes non-accrual compared to non-PIK users, while for PIK note users, the difference to non-PIK users is only 6-11pp. PIK toggle users are also 16-21pp more likely to exit the sample with a significant discount

[26]The activation of a toggle therefore resembles the "covenant-lite" dynamic in direct lending, where the absence of binding early-warning triggers shifts recognition of credit stress to later stages (Chernenko et al., 2022).

(Column (4)-(6)) relative to those that do not use PIK, while PIK-Notes these effects vary between 0-4pp and are not significantly different from zero.

In Panel B, we focus on the Post-2017 sample by augmenting the data using Martini-AI firm size and rating fixed effects. Controlling for origination-date firm size and credit ratings allows us to test whether these different outcomes merely reflect ex-ante borrower selection rather than information revelation from ex-post activation. The results confirm that ex-post PIK-toggle activation conveys distinctly negative information about deteriorating borrower prospects beyond what ex-ante screening captures, indicating that PIK-Toggles function primarily as forbearance mechanisms for fundamentally distressed borrowers rather than planned liquidity management tools. In contrast, similar to Panel A, the PIK notes convey only midly more negative information about future loan outcomes compared non-PIK'd loans.

5.2.3 Maturity extensions and debt-to-equity swaps

The evidence thus far indicates that PIK users experience persistent deterioration rather than recovery. A natural question follows: How do lenders ultimately resolve these distressed loans? Specifically, do lenders implement comprehensive restructurings that restore borrower solvency, or do they engage in forbearance by extending maturities to delay loss recognition?

Financial distress can be addressed through two distinct mechanisms. Debt-to-equity swaps reduce the borrower's outstanding debt in exchange for equity stakes, improving leverage ratios and aligning lender-borrower incentives through shared ownership. This approach acknowledges credit losses immediately but positions both parties to benefit from recovery. Alternatively, maturity extensions provide borrowers with additional repayment time without reducing debt obligations. While extensions can be appropriate when borrowers face temporary liquidity constraints, they constitute forbearance when used to avoid recognizing losses on fundamentally insolvent credits, a practice commonly termed "extend-and-pretend."

The institutional features of PIK financing create natural linkages to both mechanisms. On one hand, PIK combined with debt-to-equity swaps could represent legitimate restructuring: lenders defer cash interest to preserve borrower liquidity while injecting fresh equity (or converting debt) to improve solvency. On the other hand, PIK combined with maturity extensions may signal forbearance: lenders capitalize unpaid interest into growing principal balances and extend maturity dates to postpone default recognition, all while maintaining the pretense that debt will be repaid at par.

We test this empirically by examining whether loans experiencing PIK activation are subsequently more likely to receive (1) maturity extensions or (2) debt-to-equity swaps. We construct two outcome variables: *Maturity Extension* equals one if the loan's remaining maturity increases quarter-over-quarter, and *Debt-to-Equity Swap* equals one if a BDC's debt claim on a borrower decreases while simultaneously its equity stake increases. We then study if either of those events have happened after loan origination (at some date $\tau + m$) by using an indicator that flags such event as our dependent varibale $y_{blk,\tau+m}$. We run the following OLS regression:

$$y_{blk,\tau+m} = \beta_1\, PIK\, Toggle_{blk,\tau+n} + \beta_2\, PIK\, Note_{blk,\tau} + Controls + FEs + e_{blk,\tau}$$

and report the results in Table 8.

Loans activated with PIK Toggles are 27–30pp more likely to receive maturity extensions compared to non-PIK loans (Columns (1) to (3)), whereas PIK Notes show no significant association with maturity extensions and even a statistically significant negative relationship in Column (2). This finding is striking because it reveals a fundamental structural difference: discretionary PIK provisions (Toggles) predict forbearance-style maturity extensions, while predetermined PIK provisions (Notes) do not.

Columns (4)–(6) reveal a secondary but less pronounced response: PIK Toggle activation associates with a 8–11pp increase in debt-to-equity swaps. PIK Notes again show the opposite pattern, with a lower likelihood of debt-to-equity conversions in the baseline specifications (Columns (4) to (5)), though this effect attenuates with the addition of borrower and BDC-year-quarter fixed effects (Column (6)).

The differential magnitudes are economically significant and important. The point estimate for maturity extensions (27–30pp) exceeds that for debt-to-equity swaps (8–11pp) by a factor of 3, indicating that maturity extensions are the dominant resolution mechanism when PIK Toggles are exercised. While both outcomes occur with elevated frequency, the even higher likelihood of maturity extensions strongly supports the forbearance hypothesis: discretionary PIK largely enables lenders to postpone recognition of credit losses through repeated maturity deferrals rather than to facilitate fundamental restructurings that recapitalize distressed borrowers. This pattern is inconsistent with PIK functioning as efficient bridge financing for temporarily distressed, viable firms. Instead, it aligns with zombie lending dynamics wherein lenders extend obligations to avoid recognizing losses on inherently insolvent loans.[27]

6 How Does Deferred Interest Affect BDC Funding and Investment?

PIK provisions create a distinctive institutional friction for BDCs themselves: interest income must be recognized for tax purposes even though no cash is received. This creates a critical funding challenge. Given Registered Investment Company (RIC) requirements mandating distribution of at least 90% of net investment income as dividends, a BDC with high interest deferrals must fund distributions to shareholders from existing liquidity reserves, draw down bank credit lines, issue bonds, liquidate portfolio positions, and reduce lending, or reduce dividend payments.

How the BDCs' financiers view PIK usage has direct implications for how these flexibility provisions get financed. If BDCs' PIK offering is seen as an efficient liquidity provision tool by banks, then we would expect them to promote it by offering credit lines of PIK-heavy BDCs. Conversely, if banks contractually restrict their exposure through PIK

[27]In the Online Appendix, we support these results using survival analysis and a hazard model, which reveals that using PIK in the previous period lowers the probability of a loan exiting the sample, consistent with the view that PIK is often coupled with maturity extensions that prolong the holding period of distressed firms.

covenants, the financing pressure manifests instead as reduced asset growth, constrained credit supply to borrowers, and potentially reduces shareholder returns.

We investigate this mechanism empirically by examining three central questions: (1) Do BDCs with high PIK usage increase their reliance on bank credit lines, or do bank covenants contractually limit such reliance? (2) What contractual protections do banks employ to insulate themselves from PIK-driven financing pressure? And, (3) when banks constrain credit access to high-PIK BDCs, how do these constraints manifest in BDC balance sheet decisions—reduced asset growth, reduced lending, dividend cuts, or increased bond issuance?

6.1 BDC capital structure

BDC Collateral provides broad details on BDC capital structures, including total debt and total assets, but does not distinguish between different debt types. To obtain comprehensive information on the structure of debt, we merge BDC Collateral with CapitalIQ and the combined CRSP/Compustat database. Following Colla et al. (2013), we exclude BDC-quarter observations for which total debt reported in BDC Collateral deviates by more than 10% from the total debt reported in CapitalIQ. This process yields a matched sample of 66 unique BDCs, for which we obtain detailed quarterly data on drawn and undrawn credit lines, term loans, bonds, and commercial paper issuances from 2012Q1 through 2024Q4.

BDC capital structure. Panel A of Figure 6 shows the composition of the aggregate BDC sector's balance sheet as of the fourth quarter of 2022, providing insights into both asset holdings and funding sources.[28] On the asset side, direct lending positions comprise the vast majority (98%) of total assets, emphasizing BDCs' primary role as specialized loan providers. Only a small fraction (2%) is held in cash or cash-equivalent reserves, reflecting their strategic focus on lending rather than liquidity accumulation. Regarding liabilities and equity, nearly half (46%) of the BDCs' funding comes from shareholder

[28]This excludes the BDCs that do not report the detailed funding mix.

equity, suggesting a relatively robust capital cushion. Other debt—such as bonds, and similar capital-market instruments—accounts for another significant portion (32%) of their funding structure. Bank financing, primarily through drawn credit lines (21%) and bank term loans (1%), represents approximately one-fifth of their funding. Additionally, BDCs maintain off-balance-sheet liquidity through undrawn bank credit lines (12%), ensuring capacity for future investments and flexibility in managing short-term liquidity requirements. Overall, BDCs are highly lending-focused entities with minimal cash holdings, funded through a balanced mix of equity and diversified debt instruments. Their substantial equity base reflects regulatory and market-driven capitalization requirements, while undrawn credit lines provide critical contingent liquidity to support lending activities.

Panel B illustrates the evolution of the funding mix for a typical BDC's balance sheet (expressed as a percentage of total assets) from 2012Q1 through 2024Q4, highlighting notable trends, such as a decline in equity funding replaced by bank and nonbank debt financing.

Bank Lending to BDCs. Figure 7 illustrates trends in bank lending to Business Development Companies (BDCs) from 2013Q1 to 2024Q3. Panel A presents the evolution of outstanding bank debt, decomposed into *Committed Credit Lines*, *Drawn Credit Lines*, and *Bank Loans*. The data show a steady increase in total committed credit over the sample period, with pronounced growth beginning around 2018 and peaking in 2023 at over USD 60 billion. Drawn credit lines and bank loans followed similar upward trends, though with greater cyclicality and a recent moderation in 2024.

Panel B depicts the share of bank debt relative to total BDC debt and the utilization rate of credit lines. Bank debt share fluctuated between 0.35 and 0.55, peaking during mid-cycle expansions and declining sharply in 2020–2021. Credit line usage exhibited similar cyclical variation, with high utilization preceding declines in bank debt share. Notice also, how the decline in bank loan and credit line usage coincided with an increase in PIK usage in 2020-2021, documented in Section 3.

6.2 Deferred interest and BDC financing choices

As documented above, BDCs rely more on credit lines than cash in their liquidity management. An important question, therefore, is whether BDCs with a higher proportion of deferred interest payments exhibit greater reliance on bank-committed lines of credit, and bank debt overall as a share of total debt funding, or whether collateral restrictions and covenants imposed by banks effectively limit such reliance.

We investigate these questions using the following OLS model:

$$y_{l,t} = \beta_1 \, PIK\, usage\, share_{l,t} + Controls_{l,t} + Fixed\, Effects + e_{lt}$$

where the dependent variable $y_{l,t}$ is either *Bank Debt Share* or *Credit Line Usage*. If higher PIK usage leads the BDC to draw down more of its bank credit line and rely more on bank debt (rather than other forms such as bonds), we would expect β_1 to be positive. Conversely, if greater PIK usage reduces reliance on bank debt and increases use of alternative funding sources, we would expect β_1 to be negative. We start by showing the unconditional correlcation between bank debt reliance and PIK usage, but then add covariates that include each BDC's time-varying characteristics, such as log fund size, leverage, cash share, profitability, and log fund age, and $YearQtr$ fixed effects that control for aggregate changes in BDCs' bank debt reliance, and BDC fixed effects that control for unobservable (and time-invariant) BDC specific factors that could influence the fund's appetite for bank debt such as manager preferences and risk aversion.

Table 9 shows the results. Results, which evaluate the relationship between PIK usage and the share of bank debt in total debt, are presented in columns (1) to (3), and those that address credit line utilization are presented in columns (4) to (6).

The analysis demonstrates a statistically significant and economically substantial negative association between PIK usage and both the bank debt share and credit line usage in subsequent quarters. Specifically, the most conservative specifications in columns (3) and (6) indicate that a one percentage point increase in PIK usage leads to a 0.52 percentage point reduction in the proportion of bank debt and a 0.38 percentage point decrease in credit line utilization, both significant at the 1% threshold.

These results indicate that BDCs do not utilize bank-provided credit lines to finance PIK private credit structures. Instead, the evidence suggests that a greater reliance on PIK features serves as an indicator of heightened credit risk, leading to reduced access to bank financing and credit line drawdowns. The observed decrease in bank debt share suggests that banks are hesitant to extend credit to BDCs with substantial PIK exposure, likely due to concerns about underlying asset quality and liquidity risks. Likewise, the significant negative correlation with credit line usage indicates that BDCs with greater reliance on PIK face tighter constraints on accessing bank credit facilities when PIK is employed.

To assess this mechanism, we systematically analyze the contract terms of bank-provided credit lines to BDCs as disclosed in SEC regulatory filings. Our approach involves identifying all relevant 8-K and 8-K/A documents pertaining to bank financing and closely reviewing sections that address PIK provisions. While we allocate the details of this data collection exercise to the Online Appendix along with an example that highlights such a restriction, our review reveals that banks almost universally impose explicit limits on permissible PIK exposure, directly tying these constraints to the amount a BDC may borrow.[29] The underlying reason is that BDC investment portfolios, or discrete portions thereof, often designated as the "borrowing base", serve as collateral for bank debt. Since this collateral coverage must scale with the magnitude of outstanding borrowings, an elevated PIK usage share can restrict further bank borrowing or trigger a requirement to repay existing debt.

In summary, while BDCs receive substantial bank credit lines and exhibit higher utilization rates relative to other nonbank financial intermediaries, these contractual protections and borrowing base mechanics effectively insulate the banking sector from the risks associated with increased deferred interest payments.

[29]For the subset of BDCs with credit line outstanding, we find language restricting PIK appears in over 90% of credit line agreements. 90% is a lower bound since there may be language that refers to PIK, but which we fail to identify with our web crawler.

6.3 Deferred interest and BDC balance sheet and payout choices

In Table 10, we expand our analysis to future changes in leverage ratio (columns (1) to (2)), and cash holdings (columns (3) to (4)), log change in asset growth (columns (5) to (6)) and log change in paid dividends (columns (7) to (8)). The asset growth is based on the cost value of asset, but using the fair value would generate very similar results. The one-quarter lagged *PIK usage share* is again our key explanatory variable. We also include the same controls as in Table 9 and $YearQtr$ fixed effects. We show all the results without and with BDC fixed effects, because in the former case the coefficient reflects differences between BDCs (high-PIK BDCs vs low-PIK BDCs) plus within-BDC variation, whereas with the latter it reflects only variation within the same BDC over time, that is how outcomes change when that BDC's PIK share rises relative to its own average.

Columns (1)-(2) show that we do not find evidence that lower cash flows from high PIK usage are financed with BDCs tilting toward more leveraged capital structure. Quite the contrary, the estimate in column (2) suggests that BDCs lower their leverage ratio in the next period following high PIK usage. In columns (3) and (4), we also show that their cash share relative to total assets does not change following changes in the level of PIK usage.

In contrast, the findings in columns 5 and 6 reveal a statistically significant and negative association between PIK usage and asset growth. A one percentage point increase in PIK usage is associated with approximately 0.09 percentage point reduction in asset growth, at the 1% significance level. These results suggest that greater reliance on PIK structures constrains asset expansion, likely reflecting a deterioration in loan performance and reduced reinvestment capacity for BDCs.

Similarly, there is some evidence that PIK usage is negatively associated with dividend growth. In the baseline specification (column 7), a one percentage point increase in PIK usage is linked to approximately 0.06 percentage point reduction in dividend growth, significant at the 5% level. However, when BDC fixed effects are included (column 8), the coefficient becomes smaller (-0.02) and loses statistical significance. This attenuation suggests that the observed relationship between PIK usage and dividends may be partially explained by time-invariant BDC-specific characteristics, such as risk appetite or different approaches to payout policies.

7 Conclusion

This paper examines whether Payment-in-Kind (PIK) provisions function as efficient liquidity management or forbearance mechanisms in private credit markets. Using a new and comprehensive BDC loan data, we show PIK predominantly enables forbearance rather than temporary bridge financing.

PIK users are distressed firms lacking bank financing. PIK activation predicts persistent deterioration lasting at least two years, with loans exercising PIK Toggles ex-post exhibiting higher nonaccrual rates compared to PIK-Notes structured at origination. This pattern indicates ex-post activation reveals negative information about deteriorating creditworthiness. Cross-sectional tests show adverse effects persist regardless of maturity or size, with private equity sponsorship providing the only meaningful mitigation.

PIK-Toggle activation predicts maturity extensions far more than formal restructurings, mirroring extend-and-pretend behavior in other credit markets. Despite substantial bank lending to BDCs, covenant-based restrictions insulate banks from PIK losses—we find that credit line contracts almost universally restrict PIK collateral eligibility. PIK-heavy BDCs consequently experience reduced bank financing and respond by constraining asset growth and dividends, suggesting credit supply contraction rather than banking sector transmission.

In conclusion, while PIK provisions offer legitimate financial flexibility in narrow circumstances, our empirical analysis indicates they function primarily as forbearance mechanisms that delay recognition of fundamental distress. The sophisticated covenant structures we document suggest banks have effectively protect themselves through contractual design, but the accumulation of hidden losses in private credit portfolios and the transmission of financing constraints through credit supply channels raise important questions about systemic risks in the rapidly expanding, yet opaque, private credit market.

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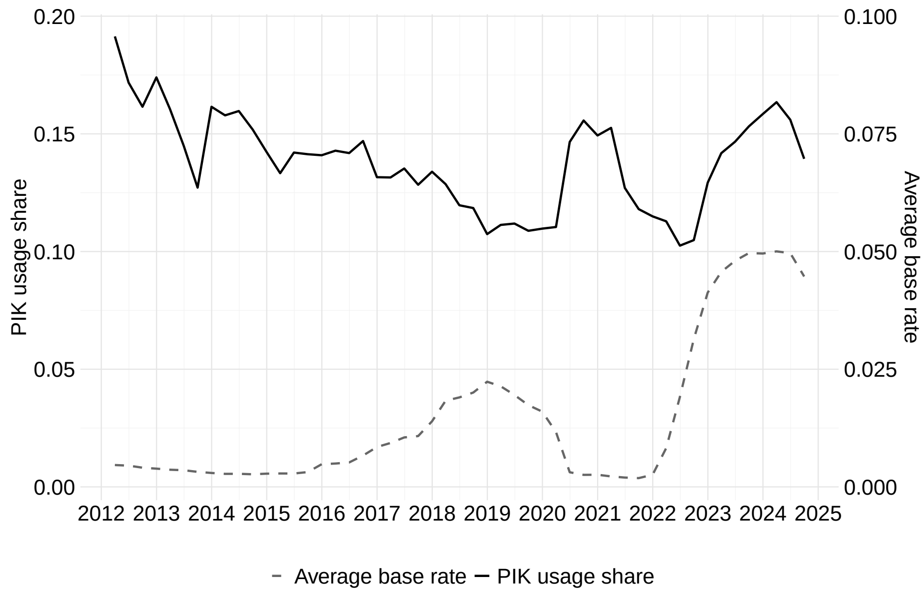
Figure 1: PIK usage across the financial cycle

Panel A shows the time-series of the PIK usage share across all BDCs' portfolio loans over the 2012Q1 to 2024Q3 period (solid line) as well as the average base rate (dashed line). PIK usage share is the value-weighted number of loans in which borrowers use PIK, relative to all loans in a given quarter. Panel B shows the PIK usage share, calculated using a value-weighted number of loans with non-accrual status or a valuation below 80%.

Panel A - PIK usage share and average base interest rate



Panel B - PIK usage share and loan distress

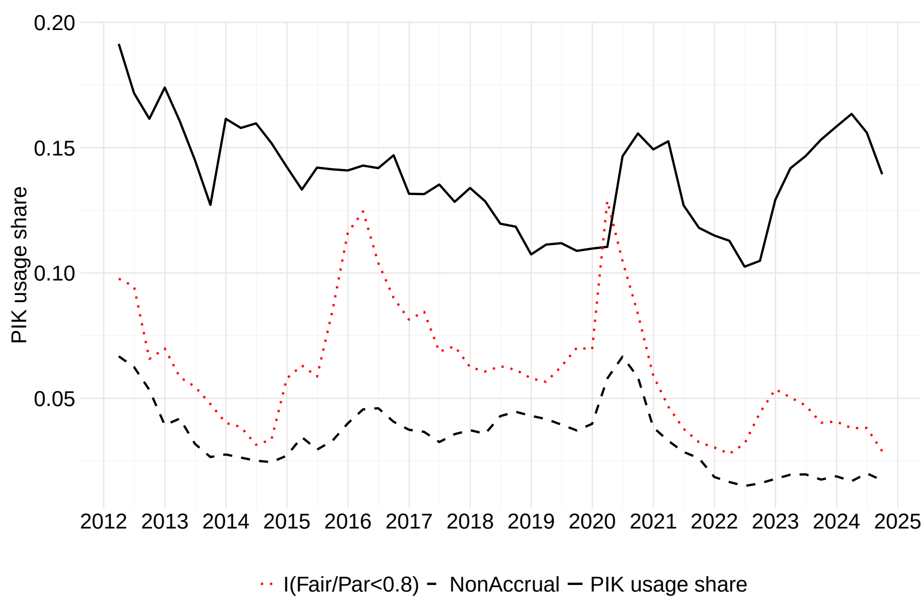
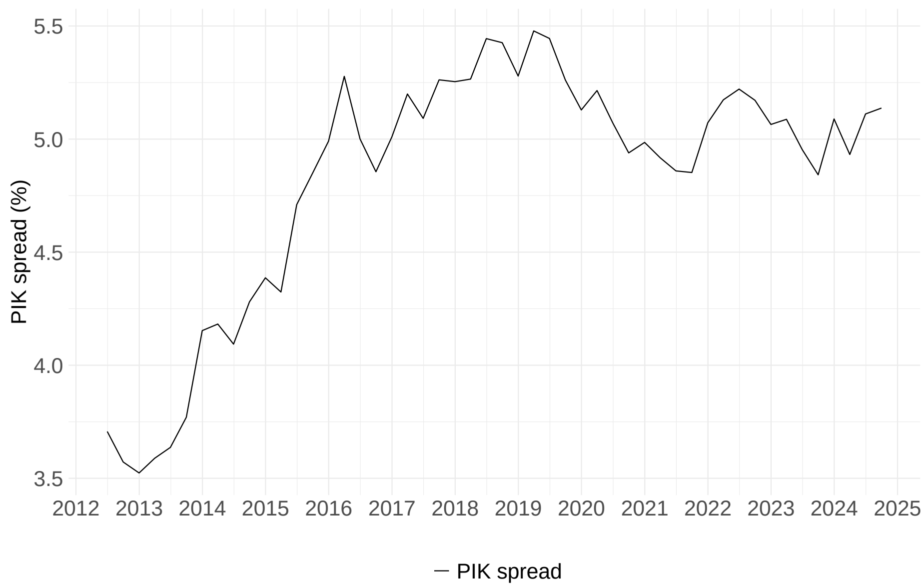


Figure 2: PIK loan characteristics

Panel A shows the equal-weighted average PIK spread among loans that use PIK.
Panel B shows the equal-weighted (EW) and par-value weighted (VW) average PIK spread relative to all-in-yield across all loans in the sample.

Panel A - Average PIK spread among active PIK loans



Panel B - Average PIK spread share relative to all-in-yield among all loans

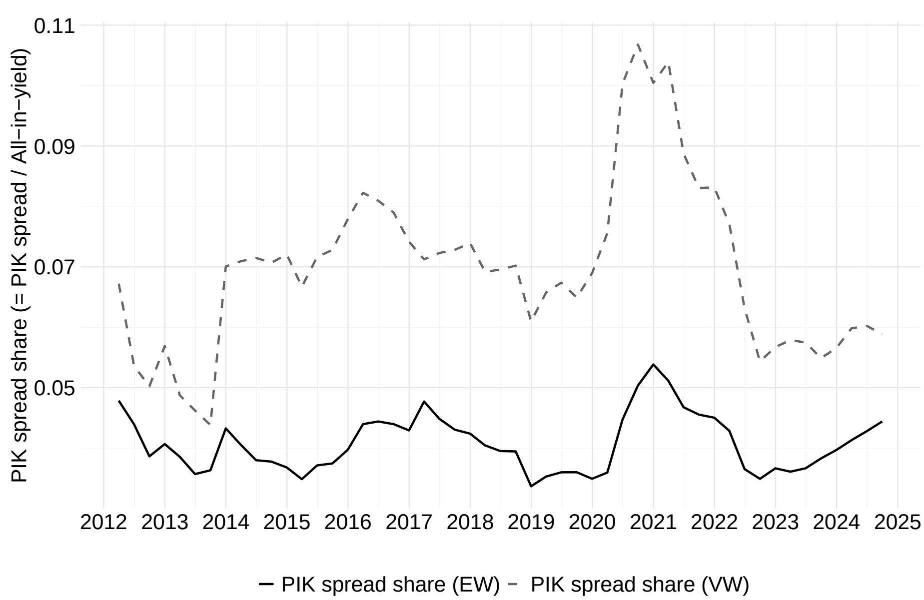
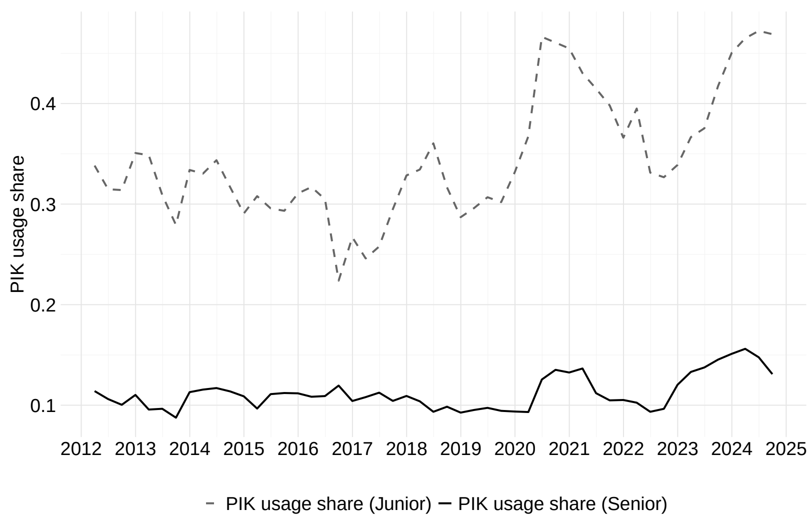


Figure 3: Heterogeneity in PIK users

Panel A decomposes the PIK usage share to senior loans, which include First Lien and Second Lien Senior Secured loans, and junior loans, which include Subordinated Debt across all BDCs' portfolio loans during the 2012Q1 to 2024Q3 period. PIK usage share is the value-weighted number of loans where borrowers use the PIK relative to all loans in a given quarter. Panel B shows the time series of the PIK usage share decomposed to loans of those borrowers who have received a bank loan within the preceding 5 years (solid line) and those who have not (dashed line). Panel C shows the PIK usage share for PIK Notes and PIK Toggle, respectively. PIK usage share for PIK toggles is the value-weighted number of loans in which borrowers use the PIK option, relative to all loans in a given quarter, while excluding PIK notes, while PIK usage share for PIK notes is the value-weighted number of loans in which borrowers use the PIK, relative to all loans in a given quarter, while excluding PIK toggles.

Panel A - PIK usage share based on loan seniority



Panel B - PIK usage among different types of borrowers

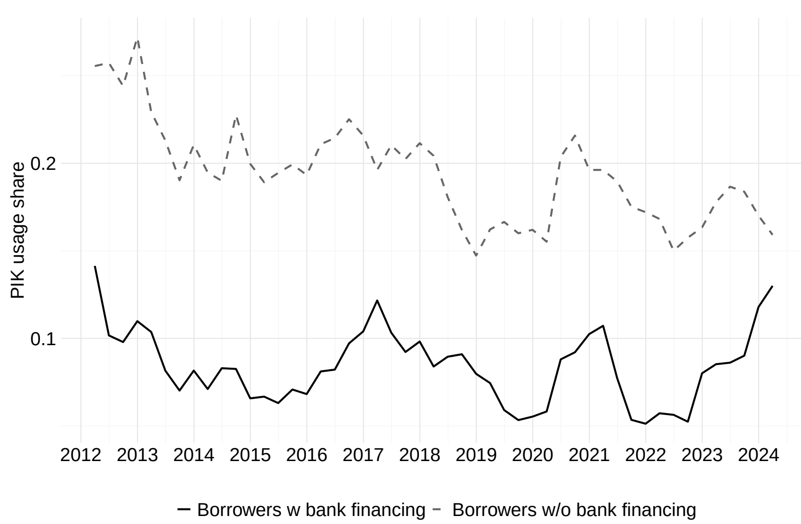


Figure 3: Heterogeneity in PIK users (continued)

Panel C - PIK usage share among PIK Notes and PIK Toggles

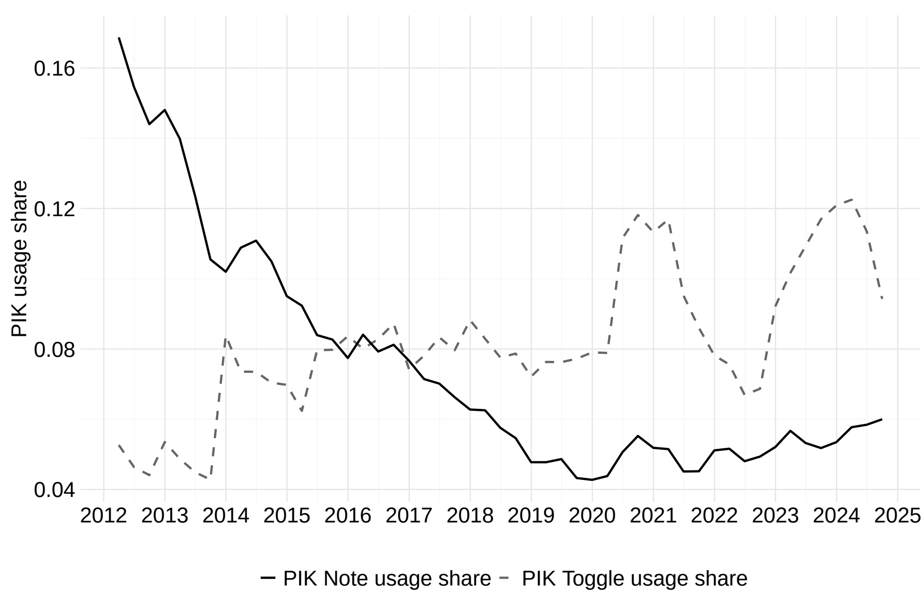


Figure 4: Impulse response functions

The figure plots the impulse response functions based on the following local-projection regression

$$y_{blk,t+h} = \beta_h PIK_{blkt} + \sum_{j=0}^{4} \gamma_{hj}\, y_{blk,t-j} + Controls + FixedEffects + e_{blk,t+h}$$

where h runs from 1 to 8 and $y_{blk,t+h}$ is either $NonAccrual$, $Fair/Par$ or $CSD(Fair/Par)$ at time $t+h$ for loan k of borrower b held by lender l. PIK_{blkt} is an indicator variable that equals one if the PIK toggle is used for loan k in time t. We include the following fixed effects: $YearQtr \times Industry + YearQtr \times BDC + Borrower \times BDC + Seniority + LoanType$. In addition to the five lagged dependent variables, we include the following controls $Ln(Loan\,Size)$ $Effective\,Base\,rate$, $Fixed\,rate\,loan$, $Ln(Time\text{-}to\text{-}Maturity)$, $Dual\,holding$, $PE\,Sponsored$, $Bank\,financing$ with all measured at time t and $All-in-spread$ measured at the origination date τ. The y-axis shows the level of the β_h coefficient, while the x-axis denotes the horizon h. The blue line represents the mean estimates, while the shaded area illustrates the 95% confidence intervals based on three-way clustered standard errors by BDC, Borrower, and year-quarter.

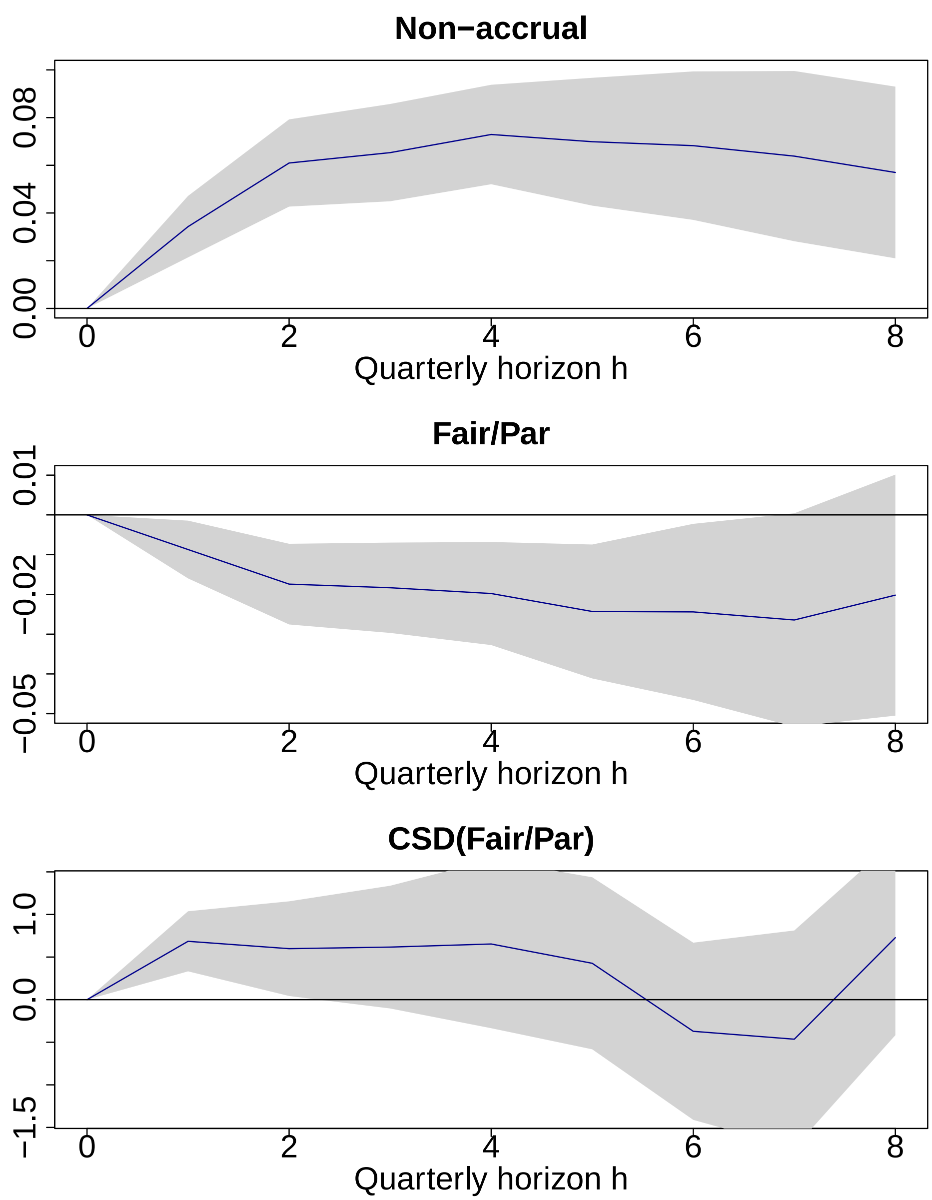
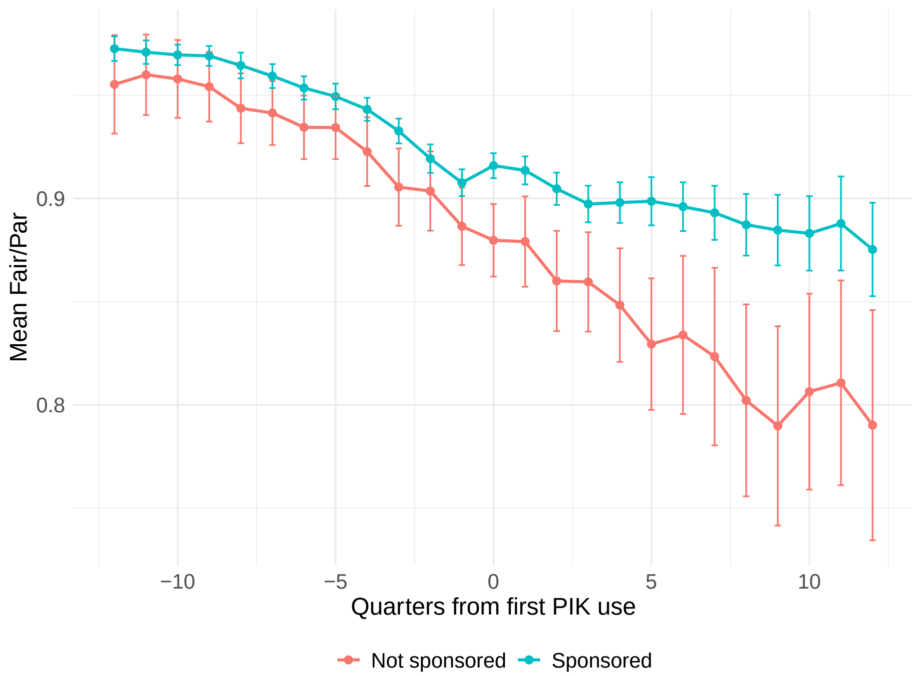


Figure 5: PE Sponsors and PIK use

Panel A - Average Fair/Par-ratio around first time of PIK use



Panel B - NonAccrual rate around first time of PIK use

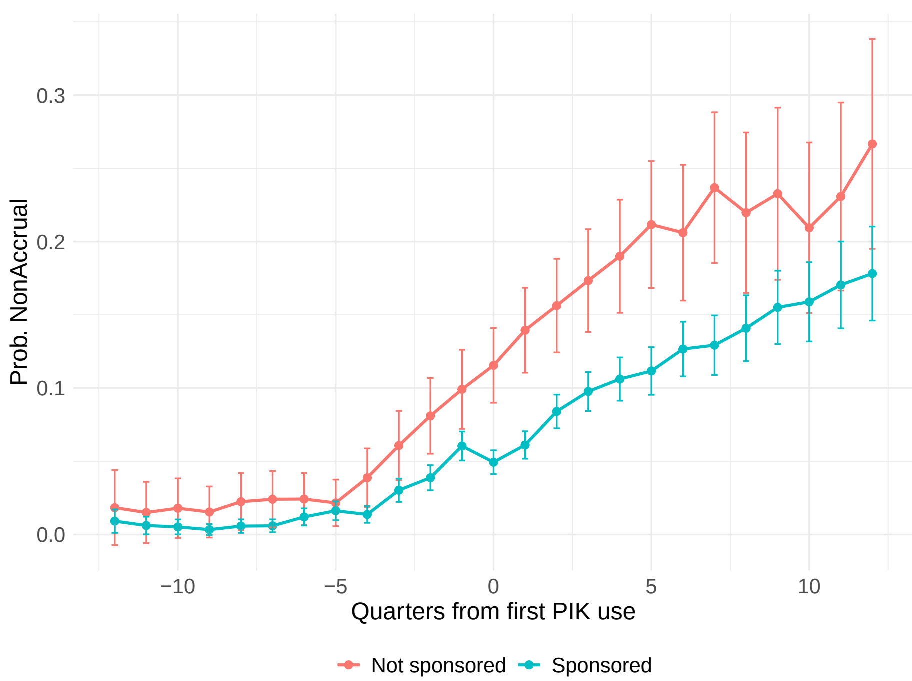
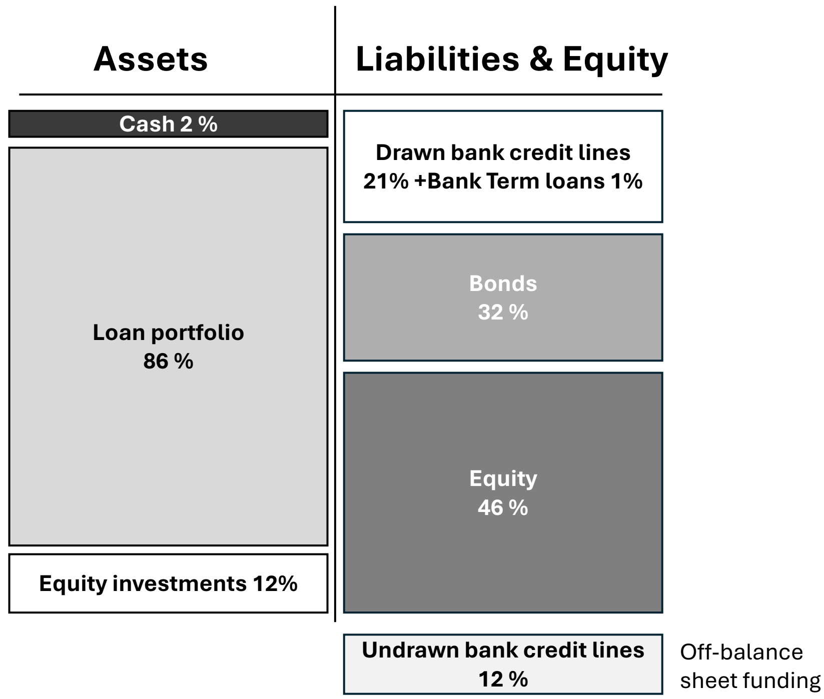


Figure 6: BDC capital structure

Panel A shows the aggregated BDC sector's balance sheet components (all relative to total assets) as of 2022Q4 for a subset of BDCs with all balance sheet data available. Panel B shows the average share of different debt structure items relative to total assets across all BDCs' balance sheets over the 2012Q1 to 2024Q3 period.

Panel B - Balance sheet of the BDC sector in 2022Q4



Panel B - BDC debt capital structure

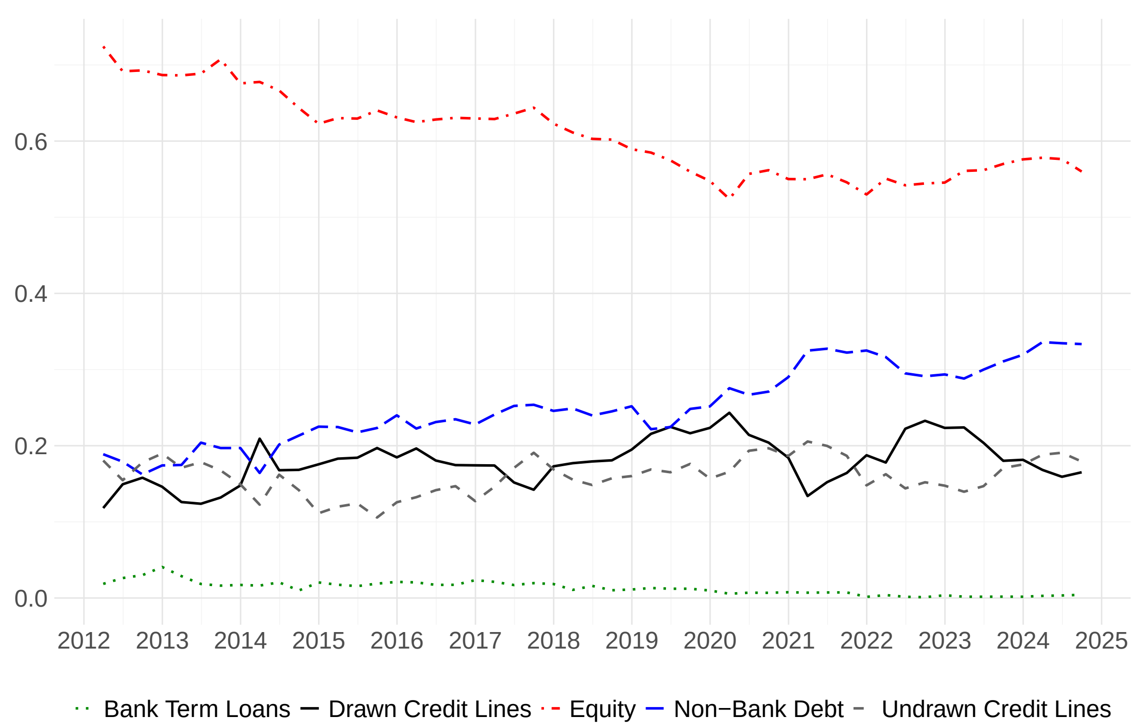
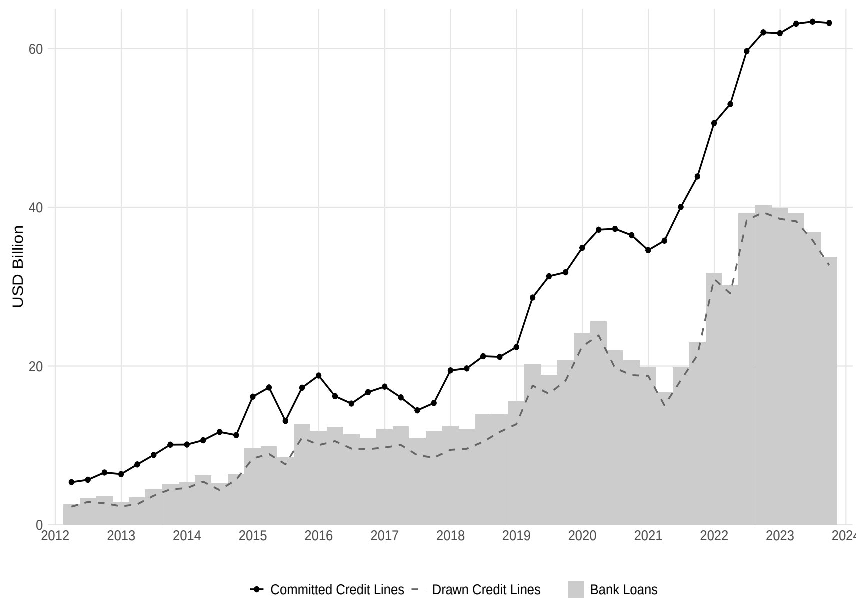


Figure 7: Bank lending to BDCs

Panel A shows outstanding bank debt of BDCs over the 2013Q1 to 2024Q3 period: *Committed Credit Lines* (the sum of drawn and undrawn credit lines), *Drawn Credit Line*s and *Bank Loans* (the sum of drawn credit lines and term loans). Panel B shows the time-series of bank debt as a percentage of total debt (*Bank debt share*) and *Credit line usage*.

Panel A - Outstanding bank debt



Panel B - Credit line usage and bank share

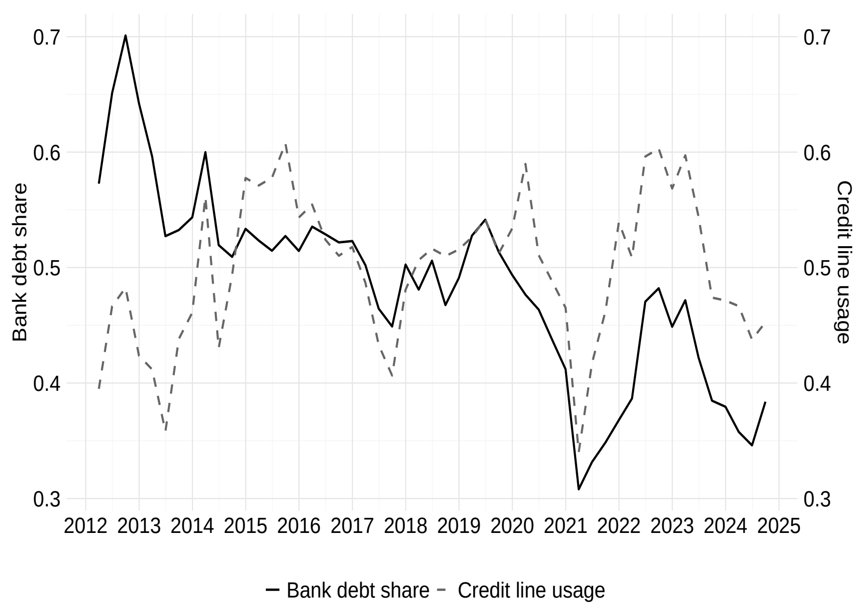


Table 1: Descriptive statistics

This table shows descriptive statistics for variables at the BDC level (Panel A) and at the loan level (Panel B). Loan is defined as a Borrower-Lender-Seniority-Loan Type -tuple. For Panels A and B, the sample period is from 2012Q1 to 2024Q4. In Panel B, when documenting the statistics of $Base\, rate$ and *All-in-spread*, we restrict the sample only to floating rate loans, and in the case of $PIK\, spread$, we focus on the observations where PIK spread is above zero. Panel C shows the share of loans with a given loan characteristic at origination for "*PIK-notes*", "*PIK-toggle*" loans, and loans with "*No PIK used*". The origination date is defined as the first date on which the loan enters the sample. *PIK-notes* are defined as loans with deferred (instead of cash interest payments) over the entire duration of the loan. *PIK-toggle* loans are loans for which borrowers do not defer interest in every period but only in some periods. *Non PIK'd loans*" refers to loans that never use PIK. For Panel C, all variables are measured at origination, except $Avg\, Cash\, Spread\, share$, $Avg\, PIK\, Spread\, share$, $Avg\, Cash\, Spread$, $Avg\, PIK\, Spread$, $Months\, in\, sample$, $Maturity\, extension$, $Share\, of\, time\, using PIK$, which are measured based on the loan's subsequent lifetime, and $I(Fair/Par < 80\%)\,(at\, termin.)$, which is measured at loan termination date, and $Future\, NonAccrual$ that is calculated from the post-origination sample. *Avg PIK spread* (*Avg Cash spread*) is the average PIK (Cash) spread during the loan's subsequent life. $Avg\, PIK\, Spread\, Share = mean(PIK\, Spread/All - in - yield)$ and $Avg\, Cash\, Spread\, Share = mean(Cash\, Spread/All - in - yield)$, with the mean calculated across the loan's subsequent life. Panel C sample excludes loans that appear in the sample for less than 4 periods, loans that originate after 2021Q4, or before 2012Q2, loans that have $Fair/Par < 0.97$ or have nonaccrual status at the implied origination date, and loans that cannot be matched to Pitchbook. For variables with missing observations, the mean is calculated by excluding these observations. Detailed variable definitions are provided in Appendix A. Column "Diff No-Toggle" ("Diff No-Note") calculates the pairwise mean-difference and associated Welch standard errors in the parentheses between loans with no PIK used and PIK toggles (respectively with no PIK used and PIK-notes).

Panel A: BDC-level panel data

Statistic	N	Mean	St. Dev.	Q1	Median	Q3
PIK usage share	3,981	0.13	0.18	0.002	0.08	0.18
Assets ($ billion)	4,465	1.60	3.83	0.25	0.59	1.62
Number of investees	4,465	84.71	74.65	32	63	119
Leverage ratio	4,465	0.40	0.17	0.33	0.44	0.51
Fund Age (in years)	4,465	9.04	11.54	3	6	11
ROE	3,497	0.06	0.17	0.02	0.09	0.14
Bank debt share	1,983	0.47	0.31	0.23	0.45	0.68
Credit line usage	1,887	0.51	0.27	0.32	0.54	0.71
Δ ln *Assets*	4,224	0.09	0.21	−0.01	0.03	0.11
Δ ln *Dividends*	3,678	0.08	0.16	−0.000	0.002	0.08

Table 1: Descriptive statistics (continued)

Panel B: Loan-level panel data

Statistic	N	Mean	St. Dev.	Q1	Median	Q3
PIK	382,239	0.10	0.30	0	0	0
All-in-yield (%)	382,239	9.53	2.81	7.68	9.75	11.30
PIK spread (%)	37,734	4.95	4.23	2.00	3.38	7.09
Cash spread (%)	382,239	6.46	2.62	5.00	6.00	7.75
All-in-spread (%)	318,366	6.24	1.99	5.25	6.00	7.25
Base rate (%)	318,366	2.95	2.12	0.65	2.80	5.09
Fixed rate loan	382,239	0.17	0.37	0	0	0
Non-accrual loan	382,239	0.03	0.16	0	0	0
Fair value ($ million)	382,239	16.01	38.81	2.18	6.68	16.49
Par value ($ million)	382,239	16.67	39.54	2.44	7.02	17.31
Cost value ($ million)	382,236	16.40	39.05	2.36	6.93	17.00
Fair/Par	382,049	0.95	0.15	0.97	0.99	1.00
Time to maturity (Months)	382,239	49.84	22.43	35.00	51.00	65.00
Dual holding	382,239	0.19	0.39	0	0	0
PE Sponsored	308,737	0.81	0.39	1	1	1
PIK Toggle loan	382,239	0.15	0.36	0	0	0
PIK Note loan	382,239	0.04	0.19	0	0	0
Bank financing	197,311	0.49	0.50	0	0	1
Number of BDC-lenders	382,239	4.07	4.75	1	2	5
Seniority classes						
First Lien Senior Secured	382,239	0.84	0.36	1	1	1
Second Lien Senior Secured	382,239	0.10	0.31	0	0	0
Subordinated Debt	382,239	0.05	0.22	0	0	0
Loan Type classes						
Revolver	382,239	0.06	0.23	0	0	0
Delay Draw Term Loan	382,239	0.07	0.26	0	0	0
Term Loan	382,239	0.80	0.40	1	1	1
Unitranche	382,239	0.06	0.24	0	0	0
Other	382,239	0.01	0.12	0	0	0

Panel C: PIK type differences

Variable	No PIK used	PIK-toggle	PIK-note	Diff No-Toggle	Diff No-Note
Observations	8730	1196	413		
First Lien Senior Secured (%)	80.3	85.8	51.1	-5.5 (1.1)	29.2 (2.5)
Fixed rate (%)	13.6	19.9	67.6	-6.3 (1.2)	-54.0 (2.3)
Par value ($ million)	14.43	19.52	18.44	-5.09 (1.28)	-4.01 (2.31)
Time-to-maturity (Months)	67.25	61.48	57.34	5.77 (0.54)	9.91 (1.03)
All-in-yield (%)	7.8	8.9	11.9	-1.1 (0.1)	-4.2 (0.2)
Avg Cash Spread (%)	6.6	6.5	6.8	0.1 (0.1)	-0.2 (0.2)
Avg PIK Spread (%)	0.0	1.9	4.5	-1.9 (0.1)	-4.5 (0.2)
Avg Cash Spread share (%)	78.9	64.8	54.3	14.2 (0.6)	24.6 (1.6)
Avg PIK Spread share (%)	0.0	16.1	37.4	-16.1 (0.5)	-37.4 (1.6)
Revolver (%)	3.4	3.6	1.0	-0.2 (0.6)	2.5 (0.5)
DDTL (%)	2.7	3.2	3.6	-0.5 (0.5)	-0.9 (0.9)
Term Loan (%)	87.3	83.9	86.7	3.4 (1.1)	0.6 (1.7)
Unitranche (%)	6.5	9.3	8.7	-2.8 (0.9)	-2.2 (1.4)
Number of BDCs	3.04	3.06	1.98	-0.02 (0.09)	1.06 (0.09)
Multiple BDCs (%)	68.9	65.1	40.7	3.7 (1.5)	28.2 (2.5)
Bank financing (%)	55.5	39.7	28.3	15.8 (1.5)	27.2 (2.3)
PE Sponsored (%)	87.6	88.5	76.3	-0.8 (1.0)	11.3 (2.1)
Dual Holding (%)	15.2	28.2	56.2	-13.0 (1.4)	-41.0 (2.5)
I(Fair/Par<80%) (at termin.) (%)	5.3	25.2	12.6	-20.0 (1.8)	-7.3 (1.9)
Future nonaccrual (%)	3.0	26.2	11.4	-23.1 (1.3)	-8.3 (1.6)
Months in sample	34.78	53.96	33.07	-19.18 (0.72)	1.72 (0.94)
Maturity extension (%)	26.4	57.2	26.9	-30.8 (1.5)	-0.4 (2.2)
Share of time using PIK (%)	0.0	41.6	100.0	-41.6 (0.8)	-100.0 (0.0)

Table 2: Use of Deferred Interest (PIK) in Private Debt

This table shows an example of loan reporting in BDC Collateral in the form of First Lien Senior Secured Term Loan to Dynamic Energy Services International from PhenixFIN BDC.

YearQtr	All-in-yield	Base rate	Effect. Base	Cash Spread	PIK Spread	PIK	Par	Fair/Par	NonAccrual	Months-to-Maturity
201401	9.5 %	0.2 %	1 %	8.5 %	0 %	0	19.00	1.00	0	48
201402	9.5 %	0.2 %	1 %	8.5 %	0 %	0	18.80	1.00	0	45
201403	9.5 %	0.2 %	1 %	8.5 %	0 %	0	18.50	1.00	0	42
201404	9.5 %	0.2 %	1 %	8.5 %	0 %	0	18.30	0.97	0	42
201501	9.5 %	0.2 %	1 %	8.5 %	0 %	0	18.00	0.98	0	36
201502	9.5 %	0.2 %	1 %	8.5 %	0 %	0	17.80	0.99	0	33
201503	9.5 %	0.2 %	1 %	8.5 %	0 %	0	17.60	0.97	0	30
201504	9.5 %	0.4 %	1 %	8.5 %	0 %	0	23.70	1.00	0	46
201601	9.5 %	0.4 %	1 %	8.5 %	0 %	0	17.10	1.00	0	24
201602	11 %	0.5 %	1 %	8.5 %	1.5 %	1	16.20	0.96	0	20
201603	11 %	0.5 %	1 %	8.5 %	1.5 %	1	16.00	0.83	0	17
201604	14.3 %	0.8 %	0.8 %	0 %	13.5 %	1	16.50	0.85	0	14
201701	14.5 %	1 %	1 %	0 %	13.5 %	1	17.00	0.85	0	11
201702	14.8 %	1.3 %	1.3 %	0 %	13.5 %	1	17.60	0.85	0	11
201703	14.8 %	1.3 %	1.3 %	0 %	13.5 %	1	18.20	0.85	0	8
201704	15.2 %	1.7 %	1.7 %	0 %	13.5 %	1	18.80	0.85	0	5
201801	15.8 %	2.3 %	2.3 %	0 %	13.5 %	1	19.50	0.61	1	13
201802	15.8 %	2.3 %	2.3 %	0 %	13.5 %	1	20.10	0.30	1	10
201803	15.9 %	2.4 %	2.4 %	0 %	13.5 %	1	21.00	0.29	1	7
201804	16.3 %	2.8 %	2.8 %	0 %	13.5 %	1	21.80	0.11	1	6
201901	16.1 %	2.6 %	2.6 %	0 %	13.5 %	1	10.40	0.11	1	34
201902	15.8 %	2.3 %	2.3 %	0 %	13.5 %	1	10.70	0.11	1	31
201903	15.6 %	2.1 %	2.1 %	0 %	13.5 %	1	11.10	0.11	1	27
201904	15.4 %	1.9 %	1.9 %	0 %	13.5 %	1	11.60	0.11	1	24
202001	14.9 %	1.4 %	1.4 %	0 %	13.5 %	1	12.00	0.07	1	21
202002	13.8 %	0.3 %	0.3 %	0 %	13.5 %	1	12.50	0.07	1	18
202003	13.7 %	0.2 %	0.2 %	0 %	13.5 %	1	12.90	0.07	1	15
202004	13.7 %	0.2 %	0.2 %	0 %	13.5 %	1	12.90	0.01	1	12
202101	13.7 %	0.2 %	0.2 %	0 %	13.5 %	1	12.90	0.00	1	9
202102	13.7 %	0.1 %	0.1 %	0 %	13.5 %	1	12.90	0.00	1	6
202103	13.6 %	0.1 %	0.1 %	0 %	13.5 %	1	12.10	0.00	1	3

Table 3: Determinants of PIK usage

This table shows the results from OLS regression of PIK use on various loan characteristics. The sample period is 2012Q1-2024Q1. PIK_{blkt} is an indicator variable that takes the value of one if the loan k from lender l to borrower b is reported to be paid in kind for period t. The sample excludes PIK Notes. $NonAccrual_{blkt}$ is an indicator variable that takes a value of one if the loan is reported as non-accrual for period t. $Ln(Time\text{-}to\text{-}Maturity_{blkt})$ is the natural logarithm of the remaining time to maturity. $I(Fair/Par_{blkt} < 0.8)$ is an indicator variable that takes a value of one if the loan's fair/par ratio is below 0.8, and zero otherwise. $Ln(Loan\,Size_{blkt})$ is the natural logarithm of the par value of the loan amount. $Fixed\,rate\,loan_{blkt}$ is an indicator variable that takes the value of one if the loan has a fixed interest rate at time t and zero otherwise. $Effec.\,Base\,rate_{blkt}$ is the maximum value between the loan k's base rate and the interest rate floor (if one exists) at time t and zero if the loan has no base rate. $All\text{-}in\text{-}spread_{blk\tau}$ is the all-in-spread at time of the origination τ. $Dual\,holding_{blt}$ is an indicator variable that takes the value of one if the BDC l also has an equity stake in the borrowing firm b. $PE\,Sponsored_{bt}$ is a dummy variable that takes a value if the borrower is private equity sponsored in period t and zero otherwise. $Bank\,financing_{bt}$ is an indicator variable that takes the value of one if the borrower has received a bank loan during the preceding five years. We exclude the intercept term from the results whenever the model has one. The last column restricts the sample to firms with multiple loans outstanding in that period. We include different fixed effect combinations. BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter e.g. 2022Q4. *Borrower* refers to the identity of the borrower. *Industry* refers to the industry of the borrower. *Seniority* refers to loan seniority. *LoanType* refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variable:				$PIK_{blk,t+1}$				
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distress								
$NonAccrual_{blkt}$	0.28***	0.19***	0.19***	0.19***	0.12***	0.12***	0.10***	0.11**
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.05)
$I(Fair/Par_{blkt} < 0.8)$		0.05***	0.05***	0.04***	0.03***	0.03***	0.03**	0.00
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Loan Terms								
$Ln(Loan\ Size_{blkt})$		0.01***	0.01***	0.01***	0.00***	0.00***	0.01***	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Ln(Time\text{-}to\text{-}Maturity_{blkt})$		-0.03***	-0.02***	-0.02***	-0.02***	-0.02***	-0.01	-0.02
		(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)
$Effec.\ Base\ rate_{blkt}$		0.39**	0.25	0.36	0.36	0.50	0.44	1.40***
		(0.18)	(0.42)	(0.44)	(0.35)	(0.33)	(0.36)	(0.46)
$Fixed\ rate\ loan_{blkt}$		0.10***	0.10***	0.11***	0.15***	0.18***	0.23***	0.16***
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
$All\text{-}in\text{-}spread_{blk\tau}$		0.26	0.37	0.38	0.35	0.36	0.73	1.16**
		(0.23)	(0.27)	(0.25)	(0.22)	(0.23)	(0.55)	(0.54)
Ownership								
$Dual\ holding_{blt}$		0.03***	0.03***	0.03***	0.02*	0.01	0.01	
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	
$PE\ Sponsored_{bt}$		0.04***	0.04**	0.04***	0.02	0.02	0.00	
		(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	
Lending Relationship								
$Ln(Number\ of\ BDCs)_{bt}$		0.00	0.00	0.00	-0.01***	-0.01***	-0.02***	
		(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	
$Bank\ financing_{bt}$		-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	
Fixed-effects								
YearQtr			Yes					
LoanType			Yes	Yes	Yes	Yes	Yes	Yes
Seniority			Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry				Yes	Yes	Yes	Yes	
Borrower					Yes	Yes		
BDC						Yes		
Borrower-BDC							Yes	Yes
YearQtr-Borrower								Yes
BDC-YearQtr								Yes
Fit statistics								
Observations	248,640	163,933	163,933	163,891	163,891	163,891	163,891	163,004
Adjusted R^2	0.03	0.08	0.09	0.10	0.50	0.50	0.55	0.80
Dependent variable mean	0.06	0.07	0.07	0.07	0.07	0.07	0.07	0.06

Table 4: Predictive regressions: PIK and loan outcomes

This table shows the results from OLS regressions of $NonAccrual_{blk,t+1}$, $Fair/Par_{blk,t+1}$ and $CSD(Fair/Par)_{bk,t+1}$ on PIK_{blkt} and various control variables. The sample period is 2012Q1-2024Q1. $NonAccrual_{blkt}$ ($NonAccrual_{blk,t+1}$)is an indicator variable that takes a value of one if the loan is reported as non-accrual for period t ($t+1$). $Fair/Par_{blkt}$ is the valuation of the loan k at time t. $CSD(Fair/Par)_{bk,t+1}$ is the cross-sectional standard deviation of similar loans' $Fair/Par$-ratio across all BDCs' portfolios at the end of period t multiplied by 100. Two loans held by two different lenders at the same time are considered similar if they are issued by the same borrower, have the same seniority, and have the same loan type. PIK_{blkt} is an indicator variable that takes the value of one if the loan k from lender l to borrower b is reported to be paid in kind for period t. The sample excludes PIK Notes. We include control variables: $Ln(Time\text{-}to\text{-}Maturity_{blkt})$ is the natural logarithm of the remaining time to maturity. $Ln(Loan\,Size_{blkt})$ is the natural logarithm of the par value of the loan amount. $Fixed\,rate\,loan_{blkt}$ is an indicator variable that takes the value of one if the loan is tied to a fixed interest rate at time t. $Effec.\,Base\,rate_{blkt}$ is the loan's base rate at time t and zero if there is no base rate. $All\text{-}in\text{-}spread_{blk\tau}$ is the all-in-spread at time when the loan k first appears in the sample at time τ. $Dual\,holding_{blt}$ is an indicator variable that takes the value of one if the BDC also has an equity stake in the borrowing firm. $PE\,Sponsored_{bt}$ is a dummy variable that takes a value if the borrower is private equity sponsored in period t and zero otherwise, an indicator for borrower b that has received $Bank\,financing_{bt}$ in the preceding 5-year period to t. We include different fixed effect combinations. BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter e.g. 2022Q4. $Borrower$ refers to the identity of the borrower. $Industry$ refers to the borrower's industry. $Seniority$ refers to loan seniority. $LoanType$ refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	$\text{NonAccrual}_{blk,t+1}$		$\text{Fair/Par}_{blk,t+1}$		$\text{CSD(Fair/Par)}_{bk,t+1}$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK_{blkt}	0.03***	0.03***	-0.01***	-0.01***	0.64***	0.64***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.17)	(0.14)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes		Yes		Yes	
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry		Yes		Yes		Yes
YearQtr-BDC		Yes		Yes		Yes
Borrower-BDC		Yes		Yes		Yes
Fit statistics						
Observations	163,973	163,931	162,705	162,663	101,304	101,298
Adjusted R^2	0.72	0.73	0.81	0.82	0.40	0.48
Dependent variable mean	0.03	0.03	0.95	0.95	1.37	1.37

Table 5: Predictive regressions: Heterogeneity in PIK'd loan outcomes

This table shows the results from OLS regressions of $NonAccrual_{blk,t+1}$ and $Fair/Par_{blk,t+1}$ on PIK_{blkt} and various control variables. The sample period is 2012Q1-2024Q1. $NonAccrual_{blkt}$ ($NonAccrual_{blk,t+1}$)is an indicator variable that takes a value of one if the loan is reported as non-accrual for period t $(t+1)$. $Fair/Par_{blkt}$ is the valuation of the loan k at time t. PIK_{blkt} is an indicator variable that takes the value of one if the loan k from lender l to borrower b is reported to be paid in kind for period t. The sample excludes PIK Notes. We include control variables: $Ln(Time-to-Maturity_{blkt})$ is the natural logarithm of the remaining time to maturity. $Ln(Loan\,Size_{blkt})$ is the natural logarithm of the par value of the loan amount. $Fixed\,rate\,loan_{blkt}$ is an indicator variable that takes the value of one if the loan is tied to a fixed interest rate at time t. $Effec.\,Base\,rate_{blkt}$ is the loan's base rate at time t and zero if there is no base rate. *All-in-spread*$_{blk\tau}$ is the all-in-spread at time when the loan k first appears in the sample at time τ. $Dual\,holding_{blt}$ is an indicator variable that takes the value of one if the BDC also has an equity stake in the borrowing firm. $PE\,Sponsored_{bt}$ is a dummy variable that takes a value if the borrower is private equity sponsored in period t and zero otherwise, an indicator for borrower b that has received $Bank\,financing_{bt}$ in the preceding 5-year period to t. We also include one-period lags of each dependent variable. The lower interaction terms and other controls are included but not shown. We include different fixed effect combinations. *BDC* refers to the identity of the BDC (Lender). *YearQtr* refers to the calendar quarter e.g. 2022Q4. *Borrower* refers to the identity of the borrower. *Industry* refers to the borrower's industry. *Seniority* refers to loan seniority. *LoanType* refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	NonAccrual$_{blk,t+1}$			Fair/Par$_{blk,t+1}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK$_{blkt}$	0.05***	0.05***	0.06	-0.02***	-0.07***	-0.09
	(0.01)	(0.02)	(0.05)	(0.01)	(0.02)	(0.06)
PIK$_{blkt}$ × PE Sponsored$_{bt}$	-0.03***	-0.02**	-0.03**	0.02***	0.01**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
PIK$_{blkt}$ × Maturity$_{blkt}$		0.00	-0.01		0.00	-0.01
		(0.00)	(0.01)		(0.00)	(0.01)
PIK$_{blkt}$ × Dual holding$_{blt}$		-0.02**	0.00		0.01	-0.01
		(0.01)	(0.01)		(0.00)	(0.01)
PIK$_{blkt}$ × Loan Size$_{blkt}$		0.00***	0.00*		0.00	0.00
		(0.00)	(0.00)		(0.00)	(0.00)
PIK$_{blkt}$ × NonAccrual$_{blkt}$		0.03*	0.07**			
		(0.02)	(0.03)			
PIK$_{blkt}$ × Fair/Par$_{blkt}$					0.07***	0.13***
					(0.02)	(0.05)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes	Yes		Yes	Yes	
Borrower	Yes	Yes		Yes	Yes	
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Borrower			Yes			Yes
YearQtr-BDC			Yes			Yes
Borrower-BDC			Yes			Yes
Fit statistics						
Observations	163,973	163,973	163,034	162,705	162,705	161,608
Adjusted R^2	0.73	0.73	0.87	0.82	0.82	0.88
Dependent variable mean	0.03	0.03	0.02	0.95	0.95	0.95

Table 6: PIK Toggles and future loan outcomes

The results are based on a lender-loan-origination level data, where origination date is defined as the date when the loan first appears in the sample in the lender's portfolio. The sample period is restricted to loan originations occurring between 2012Q2-2021Q4. $Future\,NonAccrual_{blk\tau+m}$ is an indicator variable that takes a value of one if the loan becomes nonaccrual at any date $\tau + m$ following the origination date τ, and zero otherwise. $I(Fair/Par_{blk,T} < 0.8)$ is an indicator variable that takes a value of one if the loan has a value below 80% at the last observation date T before exiting the sample and zero otherwise. $PIK\,Toggle_{blk,\tau+n}$ is an indicator variable that takes a value of one if the borrower uses its PIK toggle during the subsequent lifetime of the loan, and zero otherwise. We exclude PIK notes from the sample. Loan controls include $Ln(Time\text{-}to\text{-}Maturity)$, $Ln(Loan\,Size)$, indicator for $Fixed\,rate\,loan$, loan's *All-in-spread*, $Effec.\,Base\,rate$, indicator for presence of $Dual\,holding$, indicator for borrower's $PE\,Sponsored$ status, indicator for firm that has received $Bank\,financing$ in preceeding 5-years with all control variables measured at origination date τ and $Pre\text{-}PIK\ Amend_{bl,\tau+s}$ that is an indicator variable that takes a value of one if the loan experiences a maturity extension or becomes nonaccrual at any date $\tau + s$ following the origination date τ but preceding the earliest PIK use date $\tau + n$ (if any), and zero otherwise. All except the indicator variables are standardized (*std*) with a mean of zero and a variance of one. The lower interaction terms and other controls are included but not shown. The fixed effects: *BDC* refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter of the origination e.g. 2022Q4. $Industry$ refers to the borrower's industry. $Seniority$ refers to loan seniority. $LoanType$ refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter levels. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	Future NonAccrual$_{blk,\tau+m}$			I(Fair/Par$_{blk,T}$ <0.8)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Toggle$_{blk,\tau+n}$	0.27***	0.27***	0.35***	0.22***	0.26***	0.36***
	(0.02)	(0.02)	(0.06)	(0.03)	(0.03)	(0.08)
PIK Toggle$_{blk,\tau+n}$ × PE Sponsored$_{b\tau}$			-0.16**			-0.17**
			(0.06)			(0.07)
PIK Toggle$_{blk,\tau+n}$ × Ln(Time-to-Maturity$_{blk,\tau}$)			0.00			0.02
			(0.01)			(0.02)
PIK Toggle$_{blk,\tau+n}$ × Ln(Loan Size)$_{blk,\tau}$			0.03			0.02
			(0.02)			(0.02)
PIK Toggle$_{blk,\tau+n}$ × Dual-holding$_{bl\tau}$			0.05			0.05
			(0.05)			(0.06)
PIK Toggle$_{blk,\tau+n}$ × Pre-PIK Amend$_{blk,\tau+s}$			0.12**			0.11
			(0.05)			(0.07)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes			Yes		
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry		Yes	Yes		Yes	Yes
YearQtr-BDC		Yes	Yes		Yes	Yes
Fit statistics						
Observations	10,048	10,037	10,037	6,771	6,761	6,761
Adjusted R^2	0.20	0.29	0.30	0.11	0.18	0.19
Dependent variable mean	0.07	0.07	0.07	0.07	0.07	0.07

Table 7: Difference in loan outcomes between PIK-Notes and PIK-Toggles

The results are based on a lender-loan-origination level data, where origination date is defined as the date when the loan first appears in the sample in the lender's portfolio. The sample period is restricted to loan originations occurring between 2012Q2-2021Q4. $Future\,NonAccrual_{blk,\tau+m}$ is an indicator variable that takes a value of one if the loan becomes nonaccrual at any $\tau+m$ following the origination date τ, and zero otherwise. $I(Fair/Par_{blk,T} < 0.8)$ is an indicator variable that takes a value of one if the loan has a value below 80% at the last observation date T before exiting the sample and zero otherwise. $PIK\text{-}Toggle_{blk}$ is an indicator variable that takes a value of one if the borrower uses its PIK toggle during the subsequent lifetime of the loan, and zero otherwise, while also not being a PIK note. $PIK\text{-}Note_{blk}$ takes a value of one if the loan is classified as a PIK note, and zero otherwise. Loan controls include $Ln(Time\text{-}to\text{-}Maturity)$, $Ln(Loan\,Size)$, indicator for $Fixed\,rate\,loan$, loan's $All\text{-}in\text{-}spread$, $Effec.\,Base\,rate$, indicator for presence of $Dual\,holding$, indicator for borrower's $PE\,Sponsored$ status, indicator for firm that has received $Bank\,financing$ in preceeding 5-years with all control variables measured at origination date τ. All except the indicator variables are standardized (std) with mean zero and variance of one. The fixed effects: BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter of the origination e.g. 2022Q4. $Industry$ refers to the borrower's industry. $Seniority$ refers to loan seniority. $LoanType$ refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter levels. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A: Full sample

Dependent Variables:	Future NonAccrual$_{blk,\tau+m}$			I(Fair/Par$_{blk,T}$ < 0.8)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Note$_{blk,\tau}$	0.06***	0.04*	0.11***	0.04*	0.03	0.00
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)
PIK Toggle$_{blk,\tau+n}$	0.24***	0.26***	0.19***	0.20***	0.21***	0.16***
	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.05)
Loan controls		Yes	Yes		Yes	Yes
Fixed-effects						
YearQtr	Yes	Yes		Yes	Yes	
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry			Yes			Yes
YearQtr-BDC			Yes			Yes
Borrower			Yes			Yes
Fit statistics						
Observations	16,757	10,459	10,448	11,287	7,096	7,086
Adjusted R^2	0.11	0.14	0.65	0.06	0.08	0.45
Dependent variable mean	0.07	0.07	0.07	0.07	0.08	0.08

Table 7: Difference in loan outcomes between PIK-Notes and PIK-Toggles (continued)

Panel B: Post-2017 sample with Martini-AI firm size and rating fixed effects

Dependent Variables:	Future NonAccrual$_{blk,\tau+m}$			I(Fair/Par$_{blk,T}$ < 0.8)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Note$_{blk,\tau}$	0.05**	0.07***	0.07**	0.01	0.04	0.02
	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)	(0.04)
PIK Toggle$_{blk,\tau+n}$	0.22***	0.21***	0.21***	0.14***	0.18***	0.14***
	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)	(0.04)
Loan controls		Yes	Yes		Yes	Yes
Fixed-effects						
YearQtr	Yes			Yes		
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry		Yes	Yes		Yes	Yes
YearQtr-BDC		Yes	Yes		Yes	Yes
YearQtr-Firm Size			Yes			Yes
YearQtr-Rating			Yes			Yes
Fit statistics						
Observations	5,490	5,489	5,489	3,113	3,112	3,112
Adjusted R^2	0.11	0.19	0.21	0.05	0.12	0.10
Dependent variable mean	0.05	0.05	0.05	0.06	0.06	0.06

Table 8: PIKs, Maturity Extensions and Debt-to-Equity Swaps

The results are based on a lender-loan-origination level data, where origination date is defined as the date when the loan first appears in the sample in the lender's portfolio. The sample period is restricted to loan originations occurring between 2012Q2-2021Q4. $Maturity\,Extension_{blk,\tau+m}$ is an indicator variable that takes a value of one if the loan receives maturity extension at any date $\tau+m$ following the origination date τ, and zero otherwise. $Debt\text{-}to\text{-}Equity\,Swap_{blk,\tau+m}$ is an indicator variable that takes a value of one if the borrower receives debt to equity swap at any date $\tau+m$ following the origination date τ, and zero otherwise. $PIK\text{-}Toggle_{blk,\tau+n}$ is an indicator variable that takes a value of one if the borrower uses its PIK toggle during the subsequent lifetime of the loan, and zero otherwise, while also not being a PIK note. $PIK\text{-}Note_{blk}$ takes a value of one if the loan is classified as a PIK note, and zero otherwise. Loan controls include $Ln(Time\text{-}to\text{-}Maturity)$, $Ln(Loan\,Size)$, indicator for $Fixed\,rate\,loan$, loan's *All-in-spread*, $Effec.\,Base\,rate$, indicator for presence of $Dual\,holding$, indicator for borrower's $PE\,Sponsored$ status, indicator for firm that has received $Bank\,financing$ in preceeding 5-years with all control variables measured at origination date τ. All except the indicator variables are standardized (std) with mean zero and variance of one. The fixed effects: BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter of the origination e.g. 2022Q4. $Industry$ refers to the borrower's industry. $Seniority$ refers to loan seniority. $LoanType$ refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter levels. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	Maturity Extension$_{blk,\tau+m}$			Debt-to-Equity Swap$_{blk,\tau+m}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Toggle$_{blk,\tau+n}$	0.27***	0.27***	0.30***	0.08***	0.08***	0.11***
	(0.03)	(0.03)	(0.05)	(0.02)	(0.02)	(0.03)
PIK Note$_{blk,\tau}$	-0.04	-0.04*	0.10	-0.10***	-0.10***	0.01
	(0.03)	(0.02)	(0.08)	(0.02)	(0.02)	(0.05)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes			Yes		
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
BDC	Yes	Yes		Yes	Yes	
YearQtr-Industry		Yes	Yes		Yes	Yes
YearQtr-BDC			Yes			Yes
Borrower			Yes			Yes
Fit statistics						
Observations	10,459	10,448	10,448	10,459	10,448	10,448
Adjusted R^2	0.14	0.16	0.40	0.45	0.46	0.74
Dependent variable mean	0.30	0.30	0.30	0.15	0.15	0.15

Table 9: PIK Usage and Bank Debt Availability

This table shows the results from OLS regressions of proxies for bank debt on *PIK usage share*. *Bank debt share* is the BDC's bank debt share of total debt. *CL usage* is the BDC's share of drawn credit lines relative to total credit lines. *PIK usage share* is the par-value weighted share of portfolio companies currently paying some proportion of interest rate in-kind. All columns include the following BDC level controls: *Ln(Assets)*, *Leverage*, profitability (ROE), *Cash Share*, and *Ln(Fund Age)* all measured at $t-1$. We exclude the intercept term from the results whenever the model has one. We include different fixed effects. BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter e.g. 2022Q4. Standard errors are clustered at the BDC and year-quarter level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	Bank debt share$_{lt}$			CL usage$_{lt}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK usage share$_{lt}$	-0.66***	-0.58***	-0.51***	-0.50***	-0.44***	-0.38***
	(0.15)	(0.14)	(0.10)	(0.09)	(0.10)	(0.09)
BDC controls		Yes	Yes		Yes	Yes
Fixed-effects						
YearQtr		Yes	Yes		Yes	Yes
BDC			Yes			Yes
Fit statistics						
Observations	1,783	1,622	1,622	1,714	1,563	1,563
Adjusted R^2	0.12	0.29	0.71	0.09	0.19	0.42
Dependent variable mean	0.47	0.44	0.44	0.50	0.50	0.50

Table 10: PIKs and subsequent balance sheet and payout changes

This table shows the results from OLS regressions of BDC's asset, balance sheet, and payout changes on PIK usage share and other control variables. The results are based on BDC-quarter-level panel data. $Debt/Assets$ is the ratio between BDC's total liabilities and total assets. $\Delta\,(Debt/Assets)_{l,t+1}$ is the change in $Debt/Assets$ between quarter t and $t+1$ and correspondingly defined for $\Delta\,(Cash/Assets)_{l,t+1}$. $\Delta lnAsset_{l,t+1}$ is the log change in BDC's total assets measured in cost value. $\Delta lnDiv_{l,t+1}$ is the log change in BDC's dividends paid to shareholders. $PIK\,usage\,share_{l,t}$ is the par-value weighted share of portfolio companies currently paying some proportion of interest rate in-kind. All columns include the following BDC level controls: *Ln(Assets)*, *Leverage*, profitability (ROE), *Cash Share*, and *Ln(Fund Age)* all measured at t. We exclude the intercept term from the results whenever the model has one. We additionally include different fixed effects: BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter e.g. 2022Q4. Standard errors are clustered at the BDC, year-quarter level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	$\Delta(Debt/Assets)_{l,t+1}$		$\Delta(Cash/Assets)_{l,t+1}$		$\Delta lnAsset_{l,t+1}$		$\Delta lnDiv_{l,t+1}$	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
PIK usage share$_{lt}$	-0.01	-0.03**	0.00	0.01	-0.07***	-0.11***	-0.05*	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)	(0.03)
BDC controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects								
YearQtr	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
BDC		Yes		Yes		Yes		Yes
Fit statistics								
Observations	3,098	3,098	3,098	3,098	3,098	3,098	2,765	2,765
Adjusted R^2	0.07	0.16	0.02	0.02	0.20	0.45	0.19	0.45
Dependent variable mean	0.00	0.00	0.00	0.00	0.06	0.06	0.05	0.05

A Variable definitions

Variable	Definition	Level	Source
All-in-yield	The sum of effective base rate, cash spread, and PIK spread or the total interest rate if only that is reported.	Loan-level	BDC Collateral
All-in-spread	All-in-yield - effective base rate	Loan-level	BDC Collateral
$\Delta lnAsset$	Log change in BDC's total assets in cost value terms	Lender-level	BDC Collateral
Assets	BDC's total assets (millions USD)	Lender-level	BDC Collateral
Bank debt share	Bank debt$_t$/Total Liabilities$_t$	Lender-level	Capital IQ
Bank financing	An indicator variable that takes a value of one if the borrower has obtained a bank loan within the past 5 years and zero otherwise.	Borrower-level	Pitchbook
Base rate	The level of base rate. Zero if a fixed-rate loan.	Loan-level	BDC Collateral
Cash share	Cash/Total Assets	Lender-level	BDC Collateral
Cash spread	Cash spread for the loan over the base rate.	Loan-level	BDC Collateral
CSD(Fair/Par)	Cross-sectional standard deviation of $Fair/Par$ across lenders of loans sharing the same borrower, seniority, and loan type.	Loan-level	BDC Collateral
CL usage	Drawn credit lines/(Drawn+Undrawn credit lines)	Lender-level	Capital IQ
$\Delta lnDiv$	Log change in BDC's dividends paid to shareholders	Lender-level	BDC Collateral
Dual holding	Indicator variable that takes the value of one if the lender has equity/pref.share/warrant stake in the borrowing firm and zero otherwise	Borrower-lender-level	BDC Collateral
Debt-to-Equity Swap	Indicator variable that takes a value of one if the face value of borrower b's debt held by BDC l decreases, while simultaneously the fair value of lender l's equity stake in borrower b increases from previous period. In the cross-sectional test, the variable takes the value of one if the borrower received any debt-to-equity swap after origination, and zero otherwise.	Loan-level	BDC Collateral
Effective base rate	$\max\{\text{Base rate}, \text{Interest rate floor}\}$	Loan-level	BDC Collateral
Fair/Par	Loan's fair value to par value ratio	Loan-level	BDC Collateral
$I(Fair/Par < 0.8)$	Indicator variable that takes a value of one if the loan's fair/par ratio is below 0.8, and zero otherwise. In cross-sectional data, this is measured at the last observation date for that loan.	Loan-level	BDC Collateral
Fixed-rate loan	Indicator variable that takes the value of one if the loan is tied to a fixed rate and zero otherwise	Loan-level	BDC Collateral
Fund Age	Age of the fund in years. We use ln(1+Age) as a control variable.	Lender-level	CapitalIQ/Edgar
Future NonAccrual	An indicator variable that takes a value of one if the loan is reported as non-accrual at any date following the loan origination date, and zero otherwise.	Borrower-level	Pitchbook
Leverage ratio	Total Liabilities/Total Assets	Lender-level	BDC Collateral
Ln(Loan size)	Natural logarithm of the loan's par value	Loan-level	BDC Collateral
Ln(Time-to-Maturity)	Natural logarithm of the remaining time to maturity	Loan-level	BDC Collateral
Maturity Extension	Indicator variable that takes a value of one if the loan's remaining *time-to-maturity*$_{t-1}$ <*time-to-maturity*$_t$, and zero otherwise. In the cross-sectional test, the variable takes the value of one if maturity is ever extended after origination, and zero otherwise.	Loan-level	BDC Collateral
Non-accrual	An indicator variable that takes a value of one if the loan is reported to be non-accrual, and zero otherwise.	Loan-level	BDC Collateral
PE Sponsored	An indicator variable that takes a value of one if the borrower is PE-sponsored in a given quarter and zero otherwise.	Borrower-level	Pitchbook
PIK	Indicator variable that takes the value of one if the loan is reported to be paid in kind for that period and zero otherwise	Loan-level	BDC Collateral
PIK-Note	Indicator variable that takes a value of one for all the loan's observations if the loan is reported to be paid in kind in every period of the lifetime of the loan, and zero otherwise.	Loan-level	BDC Collateral
PIK spread	PIK spread for the loans that use PIK, zero otherwise.	Loan-level	BDC Collateral
PIK-Toggle	Same as PIK for loans other than PIK notes.	Loan-level	BDC Collateral
PIK usage share	Par-value weighted share of portfolio companies that are paying some proportion of the interest rate "in-kind".	Lender-level	BDC Collateral
ROE	Return on equity$_t$=Net income$_t$/Book Equity$_{t-1}$	Lender-level	BDC Collateral /CapitalIQ

Online Appendix

Supplementary Material for:

When Flexibility Becomes Forbearance: Payment-in-Kind in Private Credit

Paul Rintamäki & Sascha Steffen

Contents

OA.1 Data Appendix

OA.1.1 Sample Construction

This appendix outlines the data cleaning steps applied to a BDC Collateral's investment dataset, ensuring consistency, accuracy, and completeness. The process includes handling missing values, standardizing variable names, merging datasets, categorizing loan and investment types, and creating unique identifiers.

We construct the loan identifier using four identifying information: lender, borrower, seniority (e.g. "First Lien Senior Secured"), and loan type (e.g. "Term loan", "Revolver," etc). This identifier then allows us to track each loan across time. Typically, this tuple of four identifies a single loan, but in the rare cases when we observe multiple observations with the same identifier in the same year-quarter, we group these loans by summing the $Fair$, Par, and $Cost$ values of affected loans and calculating other loan characteristics as the par-value-weighted average of the loan characteristics.[1] We also remove observations with a fair/par ratio below 0 or above 500% (190 observations), since these are most likely to be data errors.

For seniority categorization, we rely on pre-existing BDC Collateral's `securitytype` classification. When creating a loan type categorization, we again mainly rely on the existing `securityclassnormalized` variable of BDC Collateral. However, due to a number of missing observations, for this category, we fill in the missing variables based on the textual information in the `securitytyperaw` variable in BDC Collateral. This variable often has textual information that helps to assign the missing observations to BDC Collateral's existing categories. For example, if the `securitytyperaw` variable contains the strings "Delay" and "Draw", we set the missing `securityclassnormalized` to "De-

[1] For example, for two loans (call them 1 and 2) with the same identifiers in the same period the new $Fair/Par$ ratio is calculated as $\frac{Fair}{Par} = \frac{Fair_1}{Par_1}\frac{Par_1}{Par_1+Par_2} + \frac{Fair_2}{Par_2}\frac{Par_2}{Par_1+Par_2}$. In most cases these loan characteristics within a tuple are typically identical or very similar anyway.

lay Draw Term Loan". We do the same for term loans, revolvers, ABL loans, bonds, unitranche loans, and letters of credit.

Finally, since this `securityclassnormalized` has several categories with only a handful of observations, such as "Aircraft Loan" with only 19 observations, we group these miscellaneous items into a larger group called "Other".[2] After this step, we have five security class categories called "Delay Draw Term Loan", "Revolver", "Term Loan", "Unitranche" and "Other". For observations with no security class information available, we allocate them to "Term Loan" category, which represents most of the loans.[3]

BDC Collateral also typically passes through the reporting errors of the SEC filings without adjustment. This requires us to make several small adjustments.

We remove some data errors. We drop observations with PIK-spread or all-in-yield over 100%. We also manually check for rounding errors and other reporting errors for several investment-level variables. For example, when the interest rates have been reported as 500% typically the correct number is 5%. In cases when the base rate is not reported at all, in the raw data, we set it to zero and assign the loan to be a fixed-rate loan, and our manual inspection verifies that the reported all-in-yield for these loans do not change between periods, even when typical reference rates like LIBOR experience shifts in levels, which vindicates this approach.[4] We also winsorize all the financial ratios (leverage, ROE, etc) at 1% and 99% level.

[2]More precisely, some of the items that we include in this category are ABL Loan, Aircraft Loans, First Out Loans, Last Out Loans, Letter of Credits, Bonds, and Other. Even after pooling, this group remains small compared to other loan type categories.

[3]Due to missing observations and heterogeneous reporting approaches of BDCs (e.g., by separating unitranche loans and term loans as separate categories that are not necessarily mutually exclusive) these Loan Type categories are unlikely to perfectly reflect the underlying loan types and should be interpreted cautiously. However, the primary purpose of this classification is to help us track each unique loan within a BDC's portfolio, and as BDCs' distinct reporting approaches are common *within* each BDC's portfolio, this classification is sufficient for our purposes.

[4]The exception is some PIK toggles, where the borrower reports a floating rate before using PIK, but stops reporting this base rate (for the period of PIK use) and instead reports a single all-in-yield. These instances suggest that floating-rate loans often switch to fixed-rate loans when PIK is used. However, even with these loans, we can track these changes with our $Fixed\,rate\,loan$ indicator variable, which is allowed to change from period to period.

Since our main focus is on private credit, we drop three BDCs that do not fit this description. We drop MacKenzie Realty Inc and Terra Income Fund 6, whose business model focuses on providing commercial real estate loans, and Newtek Business Services, which, based on our analysis and web searches, specializes in providing SBA guaranteed microloans for small businesses. [5] Even at their largest, these companies covered less than 0.7% of the total market, so dropping them has little significance on the representativeness of the sample. After dropping these three, we are left with 215 BDCs.

We use industry information associated to each borrower in LSEG BDC Collateral dataset. After unifying the writing format for the reported industres[6], there remain 30 unique industries, and they correspond closely to the standard industry classification used e.g. by credit rating agencies. For a close comparison of this industry list see e.g. Moody's, 2013. Industry information in BDC Collateral is reported for most firms—but not everyone, which is why sometimes the number of observations drops slighly when we add industry fixed effects in some the regressions.

When calculating fund age, we rely primarily on information about the date of incorporation or founding date from Pitchbook and S&P Global. However, in the absence of information from these sources, we collect the dates of BDC inception date from SEC Edgar or internet searches and use those.

OA.1.2 Pitchbook based variables

We construct several variables using data from Pitchbook and then match them to BDC Collateral data. We can find a Pitchbook ID counterpart for 13201 firms out of 16562

[5]Unlike most other BDCs that typically have approximately 100 borrowers in the portfolio, Newtek Business Services originates hundreds of tiny business loans, overwhelming the other loans in terms of number but not in economic importance. Including these loans would create unnecessary bias in any OLS estimate toward Newtek's portfolio.

[6]We make some very minor corrections to raw reporting. For example, we change the firm's industry from "Health Care" to "Healthcare" to match it with reporting format other firms.

unique borrower IDs in the BDC Collateral investment dataset.[7]

First, we control for borrowers' access to bank financing by tracking deals in Pitchbook where one of the lenders is classified as "Commercial Bank" or "Investment Bank". If the borrower has obtained a bank loan in the past five years, including the current quarter, then the variable "Bank financing" takes a value of one, and zero otherwise. We leverage the fact that our PitchBook data extends well beyond 2012 in history, which allows us to construct *Bank Financing* measure from the very beginning of our BDC Collateral sample.[8]

Second, we construct a variable "PE Sponsored" that tracks a borrower's status as a private equity-backed company. We construct this variable by using the 2024Q2 snapshot of all the firms in Pitchbook (both active and inactive ones) and then track past ownership changes using information about previous deals. We do this by first shrinking the number of potentially PE-backed firms to those firms that are assigned as "Formerly PE-backed" or "Private Equity-Backed" that is, those that are PE-backed at any point in the sample. Then we render those "Formerly PE-backed" firms as non-PE-backed from the date their ownership status changes to something else (either "Acquired/Merged", "Acquired/Merged (Operating Subsidiary)", "In IPO Registration", "Out of Business","Privately Held (no backing)", or "Publicly Held".

[7]Manual inspection of the unmatched firm IDs in BDC Collateral indicates that, from the matches that fail, often the reason is that there exists no firm name in BDC Collateral to match against, or the ID is associated with a CLO or another fund vehicle, for which Pitchbook does not offer a match. This is reassuring since our main focus is on the nonfinancial borrowers within the BDC portfolios, for which we find a match with high probability.

[8]However, there might exist another concern that we are not capturing all the bank loans of each firm, thus underestimating the share of bank financing, because Pitchbook is not capturing all the bank deals. This is certainly likely, especially with borrowers that are not tracked by Pitchbook at all. However, this concern is mitigated for two reasons. First, our sample focuses only on the firms that we can match to Pitchbook, so we are effectively looking at the firms that are on Pitchbook's radar at least. Second, we find that close to half of our sample firms are "dual (bank-and-BDC) borrowers", which closely aligns with the findings of Haque, Mayer, and Stefanescu (2024) using confidential and more comprehensive Federal Reserve Y-14 data, suggesting that within our sample, the undercapture is unlikely to be severe.

OA.1.3 Martini AI data

Martini AI is an AI-driven financial analysis firm. They provide additional information about BDCs' portfolio companies and a mapping file that matches their unique identifiers to those in BDC Collateral. Martini AI also reports static firm size information that gives an approximation of the firm's employee count. For example, they might report the employee count as "Approximately 1,500". We allocate these firm employee counts into four size groups. Firms with employee sizes of 50 or fewer are allocated into "small"-group. Firms with employee sizes between 51-1000 are allocated into the "medium"-group. Firms with employee sizes between 1001-9999 are allocated into the "large"-group. Firms with employee sizes over 10000 are allocated into the "very large"-group.

Martini AI uses its internal credit rating that resembles those used by credit rating agencies such as Moody's. The letter ratings are: A1, A2, A3, B1, B2, B3, B4, C1, C2 and D. Table A1 presents summary statistics of the loan origination level data for Martini AI variables.

OA.1.4 Construcing the loan origination sample

We construct the loan-origination level sample based on our self-constructed loan identifiers, where we identify a unique loan in our sample using *seniority* $\times$ *loan type* $\times$ *borrower* $\times$ *lender*-combo. Since there are some rare cases where an existing loan is being reported with a different loan type or seniority, this might change and rename a loan identifier to loan that has been issued earlier. To mitigate this concern that we assign an old loan as a new origination due to a change in reporting, and show statistics for a sample that is representative of the sample in our main empirical tests, we additionally apply the following filters: i) A loan's Fair/Par (which should correspond to 1 minus original issue discount, OID at new issuances) at this initial date is required to be above 0.97, as most the sample

Table A1: Use of Deferred Interest (PIK) in Private Debt: Post-2017 Sample

Panel A shows the loan characteristics of "*PIK-Notes*" and "*PIK-Toggle*" loans at origination. The origination date is defined as the first date on which the loan enters the sample. *PIK-Notes* are defined as loans with deferred (instead of cash interest payments) over the entire duration of the loan. *PIK-Toggle* loans are loans for which borrowers do not defer interest in every period but only in some periods.

Panel A: Non-PIK loans vs. PIK-Toggle Loans vs. PIK-Notes

Variable	No PIK Used	PIK-toggle	PIK-note	Diff No-Toggle	Diff No-Note
Observations	4864	1050	601		
Small (%)	13.7	12.9	22.0	0.7 (1.4)	-8.3 (3.3)
Medium (%)	48.4	55.2	61.0	-6.8 (2.1)	-12.6 (3.9)
Large (%)	27.6	27.2	13.2	0.4 (1.8)	14.4 (2.8)
Very large (%)	10.3	4.6	3.8	5.6 (0.9)	6.5 (1.6)
Rating A1 (%)	1.1	0.4	1.2	0.7 (0.3)	-0.1 (0.9)
Rating A2 (%)	0.9	0.4	0.0	0.5 (0.3)	0.9 (0.1)
Rating A3 (%)	0.4	0.0	0.6	0.4 (0.1)	-0.2 (0.6)
Rating B1 (%)	0.9	1.7	0.0	-0.8 (0.5)	0.9 (0.1)
Rating B2 (%)	6.8	6.4	8.4	0.4 (1.0)	-1.6 (2.2)
Rating B3 (%)	13.5	9.8	14.4	3.6 (1.2)	-0.9 (2.8)
Rating B4 (%)	57.6	56.3	51.5	1.3 (2.0)	6.2 (3.9)
Rating C1 (%)	10.7	18.4	13.2	-7.7 (1.5)	-2.4 (2.7)
Rating C2 (%)	6.7	4.9	8.4	1.9 (0.9)	-1.7 (2.2)
Rating D (%)	1.3	1.6	2.4	-0.3 (0.5)	-1.1 (1.2)
Probability of default (%)	0.9	0.9	0.9	-0.0 (0.1)	-0.0 (0.1)
Z-spread	0.06	0.06	0.06	-0.00 (0.00)	-0.00 (0.00)

loans rarely have OID above 3%. ii) A loan cannot be at nonaccrual status at the origination date—as the opposite case would indicate that loan is not really a new origination but an old loan that is now reported differently. iii) A loan is required to appear in the sample for at least four quarters, since we want to eliminate potential reporting errors and we are mainly interested in longer-term loans rather than temporary bridge financing loans. iv) A loan is required to be originated after 2012Q1 (as we cannot observe the implied origination date for loans that appear in the sample at the earliest sample date at 2012Q1) and before 2022Q1 (as we need a sufficiently long look-ahead horizon to study some post-origination loan outcomes). v) We need to be able to match the borrower to Pitchbook. This is primarily because all of the tests in empirical section are made with

Figure A1: Example of PIK restriction in bank credit line contract

"Collateral Portfolio" means all right, title, and interest (whether now owned or hereafter acquired or arising, and wherever located) of the Borrower in the property identified below in clauses (i) through (v) and all accounts, cash and currency, chattel paper, tangible chattel paper, electronic chattel paper, copyrights, copyright licenses, equipment, fixtures, contract rights, general intangibles, instruments, certificates of deposit, certificated securities, uncertificated securities, financial assets, securities entitlements, commercial tort claims, deposit accounts, inventory, investment property, letter-of-credit rights, software, supporting obligations, accessions, or other property consisting of, arising out of, or related to any of the following (in each case excluding the Retained Interest and the Excluded Amounts):

(i) the Loan Assets, and all monies due or to become due in payment under such Loan Assets on and after the related Cut-Off Date, including, but not limited to, all Available Collections, but excluding any related Attached Equity;

Specific Hedged Loan Assets shall be considered Fixed Rate Loan Assets or Floating Rate Loan Assets, as applicable, as provided in the definition thereof;

(vi) the aggregate Adjusted Borrowing Value of all Eligible Loan Assets that pay interest in cash less frequently than quarterly shall not exceed 15% of the aggregate Adjusted Borrowing Value of all Eligible Loan Assets;

(vii) the aggregate Outstanding Balances and Exposure Amounts of all Eligible Loan Assets that are Revolving Loan Assets and the Exposure Amounts of Eligible Loan Assets that are Delayed Draw Loan Assets shall not exceed 10% of the aggregate Adjusted Borrowing Value of all Eligible Loan Assets;

(viii) the aggregate Adjusted Borrowing Value of all Eligible Loan Assets that are Partial PIK Loan Assets shall not exceed 10% of the aggregate Adjusted Borrowing Value of all Eligible Loan Assets; and

(ix) the aggregate Adjusted Borrowing Value of all Eligible Loan Assets that are Participation Interests shall not exceed (i) during the Acquisition Participation Elevation Period, 10.0% and (ii) thereafter, 0.0%.

this sample as we need Pitchbook matching to be able to include key control variables. Our main results of this paper would be qualitatively similar without these filters.

OA.1.5 Collecting bank covenant-related information from SEC filings

BDCs' SEC 8-K filings often include information about the PIK-related covenants that banks impose on BDCs. The most ubiquitous are those that restrict the extent that collateral portfolio can contain assets that use PIK. Figure A1 gives an example of such a restriction in Ares Capital Corp's 8-K filing from June 30th, 2022, that discloses the terms of the credit line facility obtained from Wells Fargo and Bank of America. The PIK related restriction is highlighted in yellow.

To evaluate how prevalent these PIK restrictions are we used an automated Python 3 pipeline to find and collect PIK references from SEC 8-K and 8-K/A filings for Business Development Companies (BDCs). The goal was to quickly scan large numbers of filings and identify any mention of PIK terms in loan or credit agreements.

1. **Data Collection:** The process starts with an input Excel or CSV file containing BDC names and their SEC CIK numbers. Using these identifiers, the script automatically connects to the SEC EDGAR database to find all BDCs' 8-K and 8-K/A filings. File downloads were handled by the requests library.

2. **Document Retrieval:** For each filing, the script downloads its index page and uses BeautifulSoup (bs4) to find links to related exhibits such as agreements or reports.

3. **Text Extraction:** The script handls different file types: i) HTML and text files are decoded using charset-normalizer or chardet to fix encoding issues. ii) PDF files are read using pdfminer.six. If needed, pdf2image, Pillow (PIL), and pytesseract can perform OCR (optical character recognition) to extract text from image-based PDFs. All extracted text are cleaned to remove formatting and unreadable characters.

4. **Keyword and Context Search:** Clean text is searched with regular expressions (regex) for: i) Key 8-K phrases like "Entry into a Material Definitive Agreement." ii) PIK-related words such as "payment-in-kind," "PIK toggle," or "deferred interest." The script also looks for nearby financial terms like percentages, dollar amounts, or words indicating restrictions.

5. **Raw Output:** All findings are saved in structured tables using pandas, and results are exported to both Excel (.xlsx) and CSV formats with openpyxl. Each record includes the company name, CIK, filing date, document URL, detected phrase, and short text snippet for review.

6. **Identification of PIK restrictions:** From this raw data of population of 8-K filings, we drop the irrelevant filings by keeping only the filings that are associated with BDCs' credit agreements using the presence of the related keywords. From

these relevant filings we idenitfied those documents that contained discussion about PIK restrictions. Finally we read through the relevant parts (that discussed PIK) from this subset of filings using to confirm the language referred to some type of covenant associated with PIK use. Based on this information, we calculate the share of BDCs with PIK restrictions in their credit agreements relative to all BDCs with credit agreements in the SEC Edgar database.

OA.2 Additional Results

OA.2.1 BDCs in the sample as of 2024Q3

Table A2: BDCs in Sample

BDC Name	Ticker	CIK	Status	Assets (USD mn)
Blackstone Private Credit Fund	P-BCRED	1803498	Private	64 674,45
Ares Capital Corporation	ARCC	1287750	Public	27 100,00
Blue Owl Credit Income Corp. f.k.a Owl Rock Core Income Corp.	P-OLRCIC	1812554	Private	25 834,05
FS KKR Capital Corp f.k.a FS Investment Corporation	FSK	1422183	Public	15 149,00
Blue Owl Capital Corporation f.k.a Owl Rock Capital Corporation (ORCC)	OBDC	1655888	Public	14 090,78
HPS Corporate Lending Fund	P-HPSCLF	1838126	Private	13 773,40
Apollo Debt Solutions BDC	P-ADSBDC	1837532	Private	13 673,77
Blackstone Secured Lending Fund	BXSL	1736035	Public	12 371,57
Golub Capital BDC, Inc	GBDC	1476765	Public	8 705,98
Ares Strategic Income Fund	P-ARSTIF	1918712	Private	7 691,45
Prospect Capital Corporation	PSEC	1287032	Public	7 592,71
Sixth Street Lending Partners	P-SIXSLP	1925309	Private	6 731,61
Blue Owl Technology Finance Corp. f.k.a Owl Rock Technology Finance Corp.	P-ORTFIC	1747777	Private	6 685,02
North Haven Private Income Fund LLC	P-NHPIFL	1851322	Private	6 017,37
Goldman Sachs Private Credit Corp.	P-GSPCCP	1920145	Private	5 624,54
Blue Owl Technology Finance Corp. II f.k.a Owl Rock Technology Finance Corp. II	P-ORTFII	1889668	Private	5 370,75
Oaktree Strategic Credit Fund	P-OAKSCF	1872371	Private	5 223,37
Blue Owl Technology Income Corp. f.k.a Owl Rock Technology Income Corp.	P-OWLRTI	1869453	Private	5 189,14
Main Street Capital Corporation	MAIN	1396440	Public	5 094,78
Blue Owl Capital Corporation III f.k.a Owl Rock Capital Corporation III	OBDE	1807427	Public	4 464,33
MSD Investment Corp	P-MSDINC	1849894	Private	4 445,24
Franklin BSP Capital Corporation f.k.a Franklin BSP Capital L.L.C.	P-FBSPCC	1825248	Private	4 035,43
Monroe Capital Income Plus Corporation	P-MCIPCO	1742313	Private	3 817,46
Morgan Stanley Direct Lending Fund	MSDL	1782524	Public	3 793,37
Hercules Capital, Inc.	HTGC	1280784	Public	3 656,36
Goldman Sachs BDC, Inc.	GSBD	1572694	Public	3 545,49
Sixth Street Specialty Lending, Inc. f.k.a TPG Specialty Lending, Inc.	TSLX	1508655	Public	3 529,86
Golub Capital Private Credit Fund	P-GBCPCF	1930087	Private	3 513,52
New Mountain Finance Corporation	NMFC	1496099	Public	3 414,26
MidCap Financial Investment Corporation f.k.a Apollo Investment Corporation	MFIC	1278752	Public	3 216,03
Oaktree Specialty Lending Corp f.k.a Fifth Street Finance Corp.	OCSL	1414932	Public	3 198,34
Barings Private Credit Corporation	P-BARPCC	1859919	Private	3 055,14
TPG Twin Brook Capital Income Fund f.k.a AG Twin Brook Capital Income Fund	P-ATBCIF	1913724	Private	2 926,31
Barings BDC, Inc. f.k.a. Triangle Capital Corporation	BBDC	1379785	Public	2 605,08
Stone Point Credit Corporation f.k.a Stone Point Capital Credit LLC	P-STPTCC	1825384	Private	2 582,53
Bain Capital Specialty Finance, Inc	BCSF	1655050	Public	2 543,68
SLR Investment Corp. f.k.a Solar Capital Ltd.	SLRC	1418076	Public	2 442,91
Goldman Sachs Private Middle Market Credit II LLC	P-GPMMII	1772704	Private	2 397,77
Nuveen Churchill Direct Lending Corp. f.k.a Nuveen Churchill BDC Inc.	NCDL	1737924	Public	2 140,11
Blue Owl Capital Corporation II f.k.a Owl Rock Capital Corporation II	P-OWLRII	1655887	Private	2 136,67
PennantPark Floating Rate Capital Ltd.	PFLT	1504619	Public	2 108,85
T Series Middle Market Loan Fund LLC	P-TSMMLF	1885968	Private	2 083,00

Continued on next page

Table A2 (Continued)

BDC Name	Ticker	CIK	Status	Assets (USD mn)
Blackrock TCP Capital Corp. f.k.a TCP Capital Corp.	TCPC	1370755	Public	2 047,70
T. Rowe Price OHA Select Private Credit Fund	P-TRPOSF	1901164	Private	2 035,07
Kayne Anderson BDC, Inc.	KBDC	1747172	Public	2 028,25
FS Specialty Lending Fund f.k.a FS Energy and Power Fund	P-FSEN	1501729	Private	1 986,32
CION Investment Corporation	CION	1534254	Public	1 915,62
Carlyle Secured Lending, Inc. f.k.a TCG BDC, Inc	CGBD	1544206	Public	1 816,93
Carlyle Credit Solutions, Inc. f.k.a TCG BDC II, Inc.	P-TCGIII	1702510	Private	1 778,41
Trinity Capital Inc	TRIN	1786108	Public	1 734,76
AB Private Credit Investors Corporation	P-ABPCIC	1634452	Private	1 662,55
Crescent Capital BDC, Inc	CCAP	1633336	Public	1 645,05
Antares Strategic Credit Fund	P-ANSCRF	1993402	Private	1 632,63
New Mountain Guardian III BDC, L.L.C.	P-NMGIII	1781870	Private	1 607,88
Capital Southwest Corporation	CSWC	17313	Public	1 604,50
NMF SLF I, Inc.	P-NMFSLI	1766037	Private	1 507,90
Fidelity Private Credit Co LLC f.k.a Fidelity Private Credit Central Fund LLC	P-FPCRCF	1899996	Private	1 493,64
New Mountain Guardian IV BDC, L.L.C.	P-NMGBIV	1925531	Private	1 450,29
Barings Capital Investment Corporation	P-BARCIC	1811972	Private	1 436,57
Palmer Square Capital BDC Inc	PSBD	1794776	Public	1 413,55
PennantPark Investment Corp	PNNT	1383414	Public	1 389,09
Golub Capital BDC 4, Inc.	P-GCBLIV	1901612	Private	1 367,68
StepStone Private Credit Fund LLC	P-SSPCFL	1950803	Private	1 242,35
MSC Income Fund, Inc. f.k.a HMS Income Fund, Inc.	MSIF	1535778	Public	1 227,28
Saratoga Investment Corp.	SAR	1377936	Public	1 214,70
Fidelity Private Credit Fund	P-FIPRCF	1920453	Private	1 169,28
Nuveen Churchill Private Capital Income Fund	P-NCPCIF	1911066	Private	1 168,57
Fidus Investment Corporation	FDUS	1513363	Public	1 161,05
TCW Direct Lending VII LLC	P-TCWVII	1715933	Private	1 135,20
Runway Growth Finance Corp.	RWAY	1653384	Public	1 075,58
Silver Point Specialty Lending Fund	P-SRPSLF	1646614	Private	1 010,47
TCW Direct Lending VIII LLC	P-TDVIII	1825265	Private	957,51
Stellus Capital Investment Corp	SCM	1551901	Public	957,07
Middle Market Apollo Institutional Private Lending	P-MMAIPL	2006758	Private	926,28
KKR FS Income Trust	P-KKRFSI	1930679	Private	877,47
Gladstone Investment Corporation	GAIN	1321741	Public	868,78
Goldman Sachs Middle Market Lending Corp. II	P-GSMMII	1865174	Private	867,72
Diameter Credit Co	P-DIACRC	1916099	Private	843,06
BlackRock Private Credit Fund	P-BRPCRF	1902649	Private	813,78
Gladstone Capital Corporation	GLAD	1143513	Public	812,47
Varagon Capital Corp	P-VARCCP	1784700	Private	802,72
Horizon Technology Finance Corporation	HRZN	1487428	Public	793,07
TCW Direct Lending LLC	P-TCWD	1603480	Private	792,02
Oaktree Gardens OLP, LLC	P-OGOLPL	1974793	Private	787,07
Brightwood Capital Corp I	P-BRCCRPI	1895316	Private	781,59
TriplePoint Venture Growth BDC Corp.	TPVG	1580345	Public	778,35
HPS Corporate Capital Solutions Fund	P-HPSCSF	1989817	Private	730,33
Golub Capital Direct Lending Corporation	P-GCDLCP	1868878	Private	719,51
Kennedy Lewis Capital Company	P-KLCCOM	1911321	Private	714,62
KKR Enhanced US Direct Lending Fund-L Inc.	P-KKREDL	2012839	Private	710,53
Lafayette Square USA, Inc. f.k.a Lafayette Square Empire BDC, Inc.	P-LSEBDC	1849089	Private	688,41
WhiteHorse Finance, Inc.	WHF	1552198	Public	683,58

Continued on next page

Table A2 (Continued)

BDC Name	Ticker	CIK	Status	Assets (USD mn)
Jefferies Credit Partners BDC Inc.	P-JCPBDC	1959604	Private	663,75
Commonwealth Credit Partners BDC I, Inc.	P-CCPBDC	1841514	Private	653,96
First Eagle Private Credit Fund	P-FEPCRF	1890107	Private	571,10
Nuveen Churchill Private Credit Fund	P-NCPCRF	2022625	Private	555,58
26North BDC, Inc.	P-26NBDC	1950976	Private	555,29
Onex Direct Lending BDC Fund f.k.a Onex Falcon Direct Lending BDC Fund	P-OFDLBF	1860424	Private	554,05
Franklin BSP Real Estate Debt BDC	P-FBSPRE	2018545	Private	538,56
Bain Capital Private Credit	P-BACPCR	1899017	Private	533,95
Overland Advantage	P-OLDADT	1965934	Private	532,71
Monroe Capital Corporation	MRCC	1512931	Public	501,86
Phillip Street Middle Market Lending Fund LLC	P-PSMMLF	1948368	Private	491,55
OHA Senior Private Lending Fund (U) LLC	P-OSPLFL	1955010	Private	486,94
WTI Fund X, Inc.	P-WTIFXI	1850938	Private	468,42
Portman Ridge Finance Corporation f.k.a KCAP Financial, Inc.	PTMN	1372807	Public	463,67
TriplePoint Private Venture Credit Inc.	P-TPGVCL	1792509	Private	444,99
Redwood Enhanced Income Corp.	P-REDEIC	1870267	Private	433,00
Great Elm Capital Corp.	GECC	1675033	Public	427,03
Audax Credit BDC Inc.	P-ACBDCI	1633858	Private	422,26
SCP Private Credit Income BDC LLC	P-SCPPCI	1743415	Private	422,16
OFS Capital Corporation	OFS	1487918	Public	418,54
Carlyle Secured Lending III	P-CSLIII	1851277	Private	412,44
Vista Credit Strategic Lending Corp	P-VCRSLC	1919369	Private	397,35
Ares Core Infrastructure Fund	P-ARCINF	2031750	Private	364,43
Star Mountain Lower Middle-Market Capital Corp.	P-SMLMMC	1786835	Private	358,70
Silver Capital Holdings LLC	P-GSPMMC	1674760	Private	326,50
Lord Abbett Private Credit Fund	P-LAPCRF	2008748	Private	320,24
Golub Capital Direct Lending Unlevered Corp	P-GCDLUC	1901606	Private	314,08
Oxford Square Capital Corp. f.k.a TICC Capital Corp.	OXSQ	1259429	Public	312,92
New Mountain Guardian IV Income Fund, L.L.C.	P-NMGIVI	1976719	Private	311,21
KKR FS Income Trust Select	P-KKRITS	1975736	Private	310,18
PhenixFIN Corp f.k.a Medley Capital Corporation	PFX	1490349	Public	302,75
AB Private Lending Fund	P-ABPRLF	1982701	Private	289,99
Senior Credit Investments, LLC	P-SNCRIL	1959568	Private	282,04
Crescent Private Credit Income Corp.	P-CPCRIC	1954360	Private	281,83
BlackRock Direct Lending Corp	P-BRDLCO	1834543	Private	274,94
Muzinich BDC, Inc.	P-MUNBDC	1779523	Private	263,57
Stellus Private Credit BDC	P-SPCBDC	1901037	Private	262,52
Kayne DL 2021, Inc.	P-KAYDLI	1850787	Private	254,85
North Haven Private Income Fund A LLC	P-NHPIFA	1973476	Private	244,04
LGAM Private Credit LLC	P-LGAMPC	1983514	Private	237,72
SuRo Capital Corp. f.k.a Sutter Rock Capital Corp.	SSSS	1509470	Public	233,78
PIMCO Capital Solutions BDC Corp.	P-PCSBDC	1905824	Private	213,06
Investcorp Credit Management BDC, Inc. f.k.a CM Finance Inc	ICMB	1578348	Public	203,02
Venture Lending & Leasing IX, Inc.	P-VLLIXI	1717310	Private	191,85
PGIM Private Credit Fund	P-PGIMPC	1923622	Private	188,40
Logan Ridge Finance Corporation f.k.a Capitala Finance Corp	LRFC	1571329	Public	186,71
Steele Creek Capital Corporation f.k.a MSC Capital LLC	P-STCRCC	1817825	Private	172,95
AMG Comvest Senior Lending Fund	P-AMGCSL	1987221	Private	170,77
TCW Star Direct Lending LLC	P-TCWSDL	1916608	Private	147,87
BC Partners Lending Corporation	P-BCPLCO	1726548	Private	147,18

Continued on next page

Table A2 (Continued)

BDC Name	Ticker	CIK	Status	Assets (USD mn)
Manulife Private Credit Fund	P-MLPCRF	1988280	Private	131,44
Prospect Floating Rate & Alternative Income Fund, Inc.	P-PSIFIN	1521945	Private	106,32
Andalusian Credit Company, LLC	P-ADLCRC	1979306	Private	101,26
Equus Total Return, Inc.	EQS	878932	Public	95,51
Chicago Atlantic BDC, Inc. f.k.a Silver Spike Investment Corp.	LIEN	1843162	Public	89,28
BIP Ventures Evergreen BDC	P-BIPVRE	1950572	Private	87,97
Rand Capital Corporation	RAND	81955	Public	79,80
Muzinich Corporate Lending Income Fund, Inc	P-MCLIFI	1985375	Private	78,39
SLR HC BDC LLC	P-SLRHBL	1832148	Private	75,84
Wellings Real Estate Income Fund	P-WLREIF	1922947	Private	73,27
NexPoint Capital, Inc.	P-NXPTCP	1588272	Private	51,42
Hancock Park Corporate Income, Inc.	P-HPCPIN	1661306	Private	40,92
SLR Private Credit BDC II LLC	P-SLRPCB	1932591	Private	39,69
WTI Fund XI, Inc.	P-WTIXII	1987731	Private	27,60
Princeton Capital Corporation	PIAC	845385	Public	23,39
Guggenheim Credit Income Fund f.k.a Carey Credit Income Fund	P-GGCINF	1618697	Private	12,14
West Bay BDC LLC	P-WBBDCL	2020354	Private	8,24
Firsthand Technology Value Fund, Inc.	SVVC	1495584	Public	2,21
			Total Assets:	**408 352,22**

OA.2.2 Alternative definition to PIK notes and PIK Toggles

Practitioners often divide PIK loans into "Good PIK" and "Bad PIK" based on whether the loans include PIK at origination (Good) or later (Bad) (Lincoln International, 2025). This definition of "Good PIK" has a wide overlap with our baseline definition of PIK note, while "Bad PIK" has a wide overlap with our baseline definition of PIK Toggle. The only difference is that in our baseline definition, a loan that has PIK at origination but does not use it permanently and instead switches away from using PIK at some later date would be classified as a PIK Toggle and not as a PIK note. Using our origination sample as a benchmark, there are 189 such loans. Including these loans instead of our definition of PIK Note to precisely match the industry "Good PIK" definition would thus increase the number of PIK notes in our baseline sample from 413 to 602. To check if this classification matters to our results, we redo the cross-sectional tests using this alternative definition, and show that qualitatively and quantitatively, the results are very similar. In summary, the updated tables presented below show that PIK notes still have better outcomes compared to PIK notes, and the heterogeneity relating to PE-sponsored firms remains in the data, even when we study the restricted sample of PIK toggles, i.e., the "Bad PIKs".

OA.2.3 Differences in PIK usage among BDCs

Table A7 links BDC funding choices to the intensity of PIK usage. Panel A shows that, in the subsample with observed debt structure, the typical BDC finances roughly half of total assets with equity (mean 0.52; interquartile range 0.45–0.58) and the remainder primarily with debt. Within debt, drawn revolving credit lines are economically important (mean 0.18 of assets; median 0.18), while term loans play only a marginal role (mean 0.01; median 0.00). "Other debt" (which captures notes/bonds and other non-bank borrowings) is

Table A3: Descriptive statistics with alternative definition

This table shows the share of loans with a given loan characteristic at the origination date for alternative classification of "*PIK-notes*", "*PIK-toggle*" loans, and loans with "*No PIK used*". The origination date is defined as the first date on which the loan enters the sample. *PIK-notes* are defined as loans that had PIK at origination, while *PIK-toggle* loans that did not but do use PIK eventually. *Non PIK'd loans*" refers to loans that never use PIK. All variables are measured at origination, except $Avg\,Cash\,Spread\,share$, $Avg\,PIK\,Spread\,share$, $Avg\,Cash\,Spread$, $Avg\,PIK\,Spread$, $Months\,in\,sample$, $Maturity\,extension$, $Share\,of\,time\,usingPIK$, which are measured based on the loan's subsequent lifetime, and $I(Fair/Par < 80\%)\,(at\,termin.)$, which is measured at loan termination date, and $Future\,NonAccrual$ that is calculated from the post-origination sample. *Avg PIK spread* (*Avg Cash spread*) is the average PIK (Cash) spread during the loan's subsequent life. $Avg\,PIK\,Spread\,Share = mean(PIK\,Spread/All - in - yield)$ and $Avg\,Cash\,Spread\,Share = mean(Cash\,Spread/All - in - yield)$, with the mean calculated across the loan's subsequent life. Panel C sample excludes loans that appear in the sample for less than 4 periods, loans that originate after 2021Q4, or before 2012Q2, loans that have $Fair/Par < 0.97$ or have nonaccrual status at the implied origination date, and loans that cannot be matched to Pitchbook. For variables with missing observations, the mean is calculated by excluding these observations. Detailed variable definitions are provided in Appendix A. Column "Diff No-Toggle" ("Diff No-Note") calculates the pairwise mean-difference and associated Welch standard errors in the parentheses between loans with no PIK used and PIK toggles (respectively with no PIK used and PIK-notes).

Variable	No PIK Used	PIK-toggle	PIK-note	Diff No-Toggle	Diff No-Note
Observations	8808	1050	601		
First Lien Senior Secured (%)	80.4	85.6	51.3	-5.3 (1.1)	29.1 (2.5)
Fixed rate (%)	13.7	19.7	67.4	-6.0 (1.2)	-53.7 (2.3)
Par value ($ million)	14.37	19.24	18.50	-4.87 (1.24)	-4.13 (2.33)
Time-to-maturity (Months)	67.11	61.47	57.24	5.64 (0.54)	9.87 (1.03)
All-in-yield (%)	7.8	8.8	11.9	-1.1 (0.1)	-4.1 (0.2)
Avg Cash Spread (%)	6.6	6.4	6.8	0.1 (0.1)	-0.2 (0.2)
Avg PIK Spread (%)	0.0	1.8	4.5	-1.8 (0.1)	-4.5 (0.2)
Avg Cash Spread share (%)	79.0	65.1	54.5	14.0 (0.6)	24.5 (1.6)
Avg PIK Spread share (%)	0.0	15.9	37.2	-15.9 (0.5)	-37.2 (1.6)
Revolver (%)	3.8	3.6	1.2	0.2 (0.6)	2.6 (0.6)
DDTL (%)	2.8	3.2	3.6	-0.4 (0.5)	-0.8 (0.9)
Term Loan (%)	86.9	84.2	86.4	2.7 (1.1)	0.5 (1.7)
Unitranche (%)	6.5	9.0	8.8	-2.5 (0.9)	-2.3 (1.4)
Number of BDCs	3.04	3.09	1.99	-0.05 (0.09)	1.05 (0.09)
Multiple BDCs (%)	68.8	65.8	40.6	3.0 (1.4)	28.2 (2.5)
Bank financing (%)	55.4	40.7	28.2	14.7 (1.5)	27.2 (2.3)
PE Sponsored (%)	87.7	87.7	76.2	-0.0 (1.0)	11.5 (2.1)
Dual Holding (%)	15.2	27.3	56.0	-12.1 (1.3)	-40.7 (2.5)
I(Fair/Par<80%) (at termin.) (%)	5.5	27.1	12.3	-21.6 (1.8)	-6.8 (1.8)
Future nonaccrual (%)	3.4	30.2	11.2	-26.8 (1.3)	-7.8 (1.6)
Months in sample	35.07	54.92	33.41	-19.84 (0.73)	1.66 (0.95)
Maturity extension (%)	26.4	57.7	26.8	-31.3 (1.5)	-0.4 (2.2)
Debt-to-Equity Swap (%)	12.4	29.0	21.2	-16.6 (1.3)	-8.8 (2.0)
Share of time using PIK (%)	0.0	40.8	100.0	-40.8 (0.8)	-100.0 (0.0)

Table A4: PIK Toggles and future loan outcomes with alternative definition

The results are based on a lender-loan-origination level data, where origination date is defined as the date when the loan first appears in the sample in the lender's portfolio. The sample period is restricted to loan originations occurring between 2012Q2-2021Q4. $Future\,NonAccrual_{blk\tau+m}$ is an indicator variable that takes a value of one if the loan becomes nonaccrual at any date $\tau+m$ following the origination date τ, and zero otherwise. $I(Fair/Par_{blk,T} < 0.8)$ is an indicator variable that takes a value of one if the loan has a value below 80% at the last observation date T before exiting the sample and zero otherwise. $PIK\,Toggle_{blk,\tau+n}$ is an indicator variable that takes a value of one if the borrower uses its PIK toggle during the subsequent lifetime of the loan, but not at origination, and zero otherwise. We exclude PIK notes from the sample. Loan controls include *Ln*(*Time-to-Maturity*), loan $Fair/Par$ value, *Ln*(*Loan Size*), indicator for *Fixed rate loan*, loan's *All-in-yield*, indicator for presence of *Dual holding*, indicator for borrower's *PE Sponsored* status, indicator for firm that has received *Bank financing* in preceeding 5-years with all control variables measured at origination date τ and $Pre\text{-}PIK\ Amend_{bl,\tau+s}$ that is an indicator variable that takes a value of one if the loan experiences a maturity extension or becomes nonaccrual at any date $\tau+s$ following the origination date τ but preceding the earliest PIK use date $\tau+n$ (if any), and zero otherwise. All except the indicator variables are standardized (*std*) with a mean of zero and a variance of one. The lower interaction terms and other controls are included but not shown. The fixed effects: *BDC* refers to the identity of the BDC (Lender). *YearQtr* refers to the calendar quarter of the origination e.g. 2022Q4. *Industry* refers to the borrower's industry. *Seniority* refers to loan seniority. *LoanType* refers to security class e.g. Term Loan, Revolver etc. Standard errors are two-way clustered at the BDC and borrower levels. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	Future NonAccrual$_{blk,\tau+m}$			I(Fair/Par$_{blk,T}$ <0.8)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Toggle$_{blk,\tau+n}$	0.29***	0.29***	0.42***	0.25***	0.29***	0.43***
	(0.03)	(0.03)	(0.07)	(0.03)	(0.04)	(0.10)
PIK Toggle$_{blk,\tau+n}$ × PE Sponsored$_{b\tau}$			-0.20**			-0.20**
			(0.07)			(0.09)
PIK Toggle$_{blk,\tau+n}$ × Ln(Time-to-Maturity$_{blk,\tau}$)			0.00			0.02
			(0.02)			(0.02)
PIK Toggle$_{blk,\tau+n}$ × Ln(Loan Size)$_{blk,\tau}$			0.04*			0.02
			(0.02)			(0.03)
PIK Toggle$_{blk,\tau+n}$ × Dual-holding$_{bl\tau}$			0.07			
			(0.05)			
PIK Toggle$_{blk,\tau+n}$ × Pre-PIK Amend$_{blk,\tau+s}$			0.09*			
			(0.05)			
PIK_Toggle × Dual-holding$_{bl\tau}$						0.07
						(0.07)
PIK_Toggle × Pre-PIK Amend$_{blk,\tau+s}$						0.06
						(0.07)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes			Yes		
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry		Yes	Yes		Yes	Yes
YearQtr-BDC		Yes	Yes		Yes	Yes
Fit statistics						
Observations	9,858	9,847	9,847	6,655	6,645	6,645
Adjusted R^2	0.21	0.30	0.31	0.12	0.19	0.19
Dependent variable mean	0.07	0.07	0.07	0.07	0.07	0.07

Table A5: Difference in loan outcomes between PIK-Notes and PIK-Toggles with alternative definition

The results are based on a lender-loan-origination level data, where origination date is defined as the date when the loan first appears in the sample in the lender's portfolio. The sample period is restricted to loan originations occurring between 2012Q2-2021Q4. $Future\,NonAccrual_{blk,\tau+m}$ is an indicator variable that takes a value of one if the loan becomes nonaccrual at any $\tau + m$ following the origination date τ, and zero otherwise. $I(Fair/Par_{blk,T} < 0.8)$ is an indicator variable that takes a value of one if the loan has a value below 80% at the last observation date T before exiting the sample and zero otherwise. $PIK\text{-}Toggle_{blk}$ is an indicator variable that takes a value of one if the borrower uses its PIK toggle during the subsequent lifetime of the loan, but not at origination, and zero otherwise, while also not being a PIK note. $PIK\text{-}Note_{blk}$ takes a value of one if the loan is classified as a PIK note, and zero otherwise. Loan controls include $Ln(Time\text{-}to\text{-}Maturity)$, loan $Fair/Par$ value, $Ln(Loan\,Size)$, indicator for $Fixed\,rate\,loan$, loan's $All\text{-}in\text{-}yield$, indicator for presence of $Dual\,holding$, indicator for borrower's $PE\,Sponsored$ status, indicator for firm that has received $Bank\,financing$ in preceeding 5-years with all control variables measured at origination date τ. All except the indicator variables are standardized (std) with mean zero and variance of one. The fixed effects: BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter of the origination e.g. 2022Q4. $Industry$ refers to the borrower's industry. $Seniority$ refers to loan seniority. $LoanType$ refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter levels. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A: Full sample

Dependent Variables:	Future NonAccrual$_{blk\tau}$			I(Fair/Par$_{blk,T}$ < 0.8)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Note$_{blk,\tau}$	0.08***	0.04**	0.09***	0.04**	0.02	-0.04
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.04)
PIK Toggle$_{blk,\tau+n}$	0.27***	0.29***	0.21***	0.24***	0.25***	0.19***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)
Loan controls		Yes	Yes		Yes	Yes
Fixed-effects						
YearQtr	Yes	Yes		Yes	Yes	
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry			Yes			Yes
YearQtr-BDC			Yes			Yes
Borrower			Yes			Yes
Fit statistics						
Observations	16,757	10,459	10,448	11,287	7,096	7,086
Adjusted R^2	0.12	0.15	0.65	0.07	0.09	0.45
Dependent variable mean	0.07	0.07	0.07	0.07	0.08	0.08

Table A5: Difference in loan outcomes between PIK-Notes and PIK-Toggles with alternative definition (continued)

Panel B: Post-2017 sample with Martini-AI firm size and rating fixed effects

Dependent Variables:	Future NonAccrual$_{blk\tau}$			I(Fair/Par$_{blk,T}$ < 0.8)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Note$_{blk,\tau}$	0.06**	0.04	0.03	0.01	0.02	0.00
	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
PIK Toggle$_{blk,\tau+n}$	0.24***	0.24***	0.23***	0.16***	0.20***	0.17***
	(0.03)	(0.03)	(0.04)	(0.04)	(0.05)	(0.05)
Loan controls		Yes	Yes		Yes	Yes
Fixed-effects						
YearQtr	Yes			Yes		
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
YearQtr-Industry		Yes	Yes		Yes	Yes
YearQtr-BDC		Yes	Yes		Yes	Yes
YearQtr-Firm Size			Yes			Yes
YearQtr-Rating			Yes			Yes
Fit statistics						
Observations	5,490	5,489	5,489	3,113	3,112	3,112
Adjusted R^2	0.12	0.20	0.22	0.05	0.13	0.10
Dependent variable mean	0.05	0.05	0.05	0.06	0.06	0.06

Table A6: PIKs, Maturity Extensions and Debt-to-Equity Swaps with alternative definition

The results are based on a lender-loan-origination level data, where origination date is defined as the date when the loan first appears in the sample in the lender's portfolio. The sample period is restricted to loan originations occurring between 2012Q2-2021Q4. $Maturity\,Extension_{blk,\tau+m}$ is an indicator variable that takes a value of one if the loan receives maturity extension at any date $\tau+m$ following the origination date τ, and zero otherwise. *Debt-to-Equity Swap*$_{blk,\tau+m}$ is an indicator variable that takes a value of one if the borrower receives debt to equity swap at any date $\tau+m$ following the origination date τ, and zero otherwise. $PIK\text{-}Toggle_{blk,\tau+n}$ is an indicator variable that takes a value of one if the borrower uses its PIK toggle during the subsequent lifetime of the loan, and zero otherwise, but not at origination, while also not being a PIK note. $PIK\text{-}Note_{blk}$ takes a value of one if the loan is classified as a PIK note, and zero otherwise. Loan controls include $Ln(Time\,to\,Maturity)$, loan $Fair/Par$ value, $Ln(Loan\,Size)$, indicator for $Fixed\,rate\,loan$, loan's *All-in-yield*, indicator for presence of $Dual\,holding$, indicator for borrower's $PE\,Sponsored$ status, indicator for firm that has received $Bank\,financing$ in preceeding 5-years with all control variables measured at origination date τ. All except the indicator variables are standardized (std) with mean zero and variance of one. The fixed effects: BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter of the origination e.g. 2022Q4. $Industry$ refers to the borrower's industry. $Seniority$ refers to loan seniority. $LoanType$ refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter levels. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variables:	Maturity Extension$_{blk,\tau+n}$			Debt-to-Equity Swap$_{blk,\tau+n}$		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
PIK Toggle$_{blk,\tau+n}$	0.27***	0.27***	0.27***	0.09***	0.09***	0.10***
	(0.03)	(0.03)	(0.05)	(0.02)	(0.02)	(0.03)
PIK Note$_{blk,\tau}$	0.07**	0.06**	0.27***	-0.06**	-0.07**	0.08
	(0.03)	(0.03)	(0.06)	(0.03)	(0.03)	(0.05)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
YearQtr	Yes			Yes		
LoanType	Yes	Yes	Yes	Yes	Yes	Yes
Seniority	Yes	Yes	Yes	Yes	Yes	Yes
BDC	Yes	Yes		Yes	Yes	
YearQtr-Industry		Yes	Yes		Yes	Yes
YearQtr-BDC			Yes			Yes
Borrower			Yes			Yes
Fit statistics						
Observations	10,459	10,448	10,448	10,459	10,448	10,448
Adjusted R^2	0.14	0.16	0.39	0.45	0.46	0.74
Dependent variable mean	0.30	0.30	0.30	0.15	0.15	0.15

sizable (mean 0.27; median 0.26). Liquidity buffers are modest on balance sheet (cash mean 0.04; median 0.02), but BDCs maintain meaningful off-balance-sheet capacity through undrawn credit lines (mean 0.16; median 0.13), consistent with revolving facilities serving as a key liquidity backstop.

Panel B indicates systematic differences between low- and high-PIK BDCs. High-PIK BDCs are substantially larger: the 0.749 difference in log assets implies assets that are roughly twice as large as those of low-PIK peers ($= e^{0.749} = 2.1$). High-PIK BDCs also operate with higher leverage (0.430 vs. 0.389), yet do not exhibit statistically different ROE, suggesting that higher PIK usage is not associated with higher contemporaneous equity profitability in these unconditional comparisons. The most pronounced contrasts are in liability composition and liquidity: relative to low-PIK BDCs, high-PIK BDCs rely less on bank-intermediated funding (bank debt/assets lower by 0.057; drawn credit lines/assets lower by 0.061) and hold less cash (0.033), while substituting toward bond financing (bonds/assets higher by 0.089). Undrawn credit line capacity is not significantly different across groups, implying that high-PIK BDCs do not offset lower cash holdings with greater unused bank commitments. Overall, the pattern is consistent with high PIK usage coexisting with a more market-based funding mix (greater bond reliance) and weaker on-balance-sheet liquidity.

OA.2.4 PIK use with distressed borrowers and distressed BDCs

Many theories of zombie lending suggest that it is driven by lenders' risk-shifting incentives, and zombie lending to distressed firms gets amplified when the lender is undercapitalized. In Table A8, we test this by extending the results in Table 3. Specifically, we test whether BDCs with weak balance sheets, measured by high leverage, high share of nonaccrual assets, or low portfolio valuation, are more likely to offer PIK extension to borrowers that are in nonaccrual status. We measure these based on whether the attribute for a given

Table A7: BDC funding structure and its relationship with PIK usage

Panel A shows the liability structure of BDCs for that part of the sample where we observe the debt structure. Panel B shows the mean difference between BDCs grouped based on above and below median PIK usage for each period for the full sample available for each variable. The sample period is 2012Q1-2024Q4. Standard errors are clustered at the BDC and year-quarter level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Panel A: BDC Liability structure (% of total assets)

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
Bank Loans						
Drawn credit lines	1,893	0.18	0.13	0.08	0.18	0.27
Term loans	1,893	0.01	0.04	0.00	0.00	0.00
Other debt	1,895	0.27	0.15	0.15	0.26	0.38
Equity	1,896	0.52	0.09	0.45	0.52	0.58
Off-balance sheet						
Undrawn credit lines	1,896	0.16	0.12	0.08	0.13	0.21
Cash	1,896	0.04	0.05	0.01	0.02	0.05

Panel B: Mean Differences in BDC characteristics by PIK Usage

	Group Means		
Variable	Low PIK	High PIK	Difference
Ln Total Assets	6.071	6.819	0.749***
			(0.157)
Leverage Ratio	0.389	0.43	0.041***
			(0.016)
Return on Equity	0.066	0.062	-0.004
			(0.012)
Bank Debt / Assets	0.234	0.177	-0.057***
			(0.022)
Cash / Assets	0.086	0.053	-0.033***
			(0.007)
Bonds / Assets	0.205	0.294	0.089***
			(0.025)
Undrawn Credit Lines / Assets	0.167	0.157	-0.011
			(0.019)
Draw Credit Lines / Assets	0.224	0.163	-0.061***

BDC-lender l exceeds the median level of that attribute among all BDCs for that period t. We also include a "Public BDC" dummy in the list that takes a value of one if the BDC l is publicly traded in that period t, zero otherwise. When we add these interaction terms with these "weak-BDC" dummies and loan nonaccrual status, we find no evidence that BDCs with weaker balance sheets are more likely to be accommodating the PIK provision for distressed firms. In the case of public BDCs, there is some *weak* evidence that they offer more PIK use to distressed borrowers, but even this result disappears once we include all the interactions in the same specification.

OA.2.5 Survival model

To study whether payment-in-kind (PIK) usage is associated with the duration of observed loan relationships, we estimate Cox proportional hazards models on a quarterly, loan-level panel (Table A9). The event of interest is loan exit (termination) from the sample, measured as the number of quarters until termination; relationships that remain active through the end of the observation window are treated as right-censored. The Cox framework leaves the baseline hazard unspecified and identifies covariate effects through the partial likelihood. All explanatory variables are lagged one quarter ($t-1$) to mitigate simultaneity concerns. The key regressor is an indicator for PIK use, while controls include the all-in yield, non-accrual status, log loan size, and log(1+time-to-maturity). To address unobserved heterogeneity in underlying exit propensities, the baseline hazard is stratified by origination year in all specifications and further stratified by industry and BDC in columns (2) and (3), respectively. Standard errors are clustered at the borrower level. Coefficients are reported as hazard ratios (HRs), so values below one indicate a lower instantaneous exit rate (i.e., longer expected time in sample), holding other covariates constant.

Across all specifications, PIK use is associated with a materially lower hazard of loan

Table A8: Determinants of distressed firms' PIK usage: BDC implied Heterogeneity

This table shows the results from OLS regression of PIK use on various loan characteristics. The sample period is 2012Q1-2024Q1. PIK_{blkt} is an indicator variable that takes the value of one if the loan k from lender l to borrower b is reported to be paid in kind for period t. The sample excludes PIK Notes. $NonAccrual_{blkt}$ is an indicator variable that takes a value of one if the loan is reported as non-accrual for period t. $Ln(Time\text{-}to\text{-}Maturity_{blkt})$ is the natural logarithm of the remaining time to maturity. $I(Fair/Par_{blkt} < 0.8)$ is an indicator variable that takes a value of one if the loan's fair/par ratio is below 0.8, and zero otherwise. $Ln(Loan\,Size_{blkt})$ is the natural logarithm of the par value of the loan amount. $Fixed\,rate\,loan_{blkt}$ is an indicator variable that takes the value of one if the loan has a fixed interest rate at time t and zero otherwise. $Effec.\,Base\,rate_{blkt}$ is the maximum value between the loan k's base rate and the interest rate floor (if one exists) at time t and zero if the loan has no base rate. $All\text{-}in\text{-}spread_{blk\tau}$ is the all-in-spread at time of the origination τ. $Dual\,holding_{blt}$ is an indicator variable that takes the value of one if the BDC l also has an equity stake in the borrowing firm b. $PE\,Sponsored_{bt}$ is a dummy variable that takes a value if the borrower is private equity sponsored in period t and zero otherwise. $Bank\,financing_{bt}$ is an indicator variable that takes the value of one if the borrower has received a bank loan during the preceding five years. $BDC\,w/\,High\,Leverage_{lt}$, $BDC\,w/\,High\,NonAccrual_{lt}$ are indicator variables that take a value of one if the lender-BDC l is above (below for $BDC\,w/\,Low\,Fair/Cost_{lt}$) of the median value of BDC leverage or nonacrrual rate (or loan portfolio fair/par ratio) respectively at time t and zero otherwise. The $Public\,BDC_{lt}$ takes a value of one if the BDC l is publicly traded at time t and zero otherwise. We include different fixed effect combinations. BDC refers to the identity of the BDC (Lender). $YearQtr$ refers to the calendar quarter e.g. 2022Q4. *Borrower* refers to the identity of the borrower. *Industry* refers to the industry of the borrower. *Seniority* refers to loan seniority. *LoanType* refers to security class e.g. Term Loan, Revolver etc. Standard errors are clustered at the BDC, borrower, and year-quarter level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Dependent Variable:			$PIK_{blk,t+1}$		
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
$NonAccrual_{blkt}$	0.06*	0.09*	0.01	0.00	0.01
	(0.03)	(0.05)	(0.05)	(0.03)	(0.05)
$NonAccrual_{blkt}$ × BDC w/ High $Leverage_{lt}$	-0.01				-0.03
	(0.03)				(0.03)
$NonAccrual_{blkt}$ × BDC w/ Low $Fair/Cost_{lt}$		-0.06*			-0.05*
		(0.03)			(0.03)
$NonAccrual_{blkt}$ × BDC w/ High $Nonaccrual_{lt}$			0.05		0.05
			(0.04)		(0.04)
$NonAccrual_{blkt}$ × Public BDC_{lt}				0.07	0.06
				(0.05)	(0.05)
I($Fair/Par_{blkt}$ < 0.8)	0.03**	0.03**	0.03*	0.03**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Ln(Loan $Size_{blkt}$)	0.01***	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln(Time-to-$Maturity_{blkt}$)	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Effec. Base $rate_{blkt}$	0.90*	0.95**	0.91*	0.93*	0.97**
	(0.47)	(0.47)	(0.47)	(0.48)	(0.48)
Fixed rate $loan_{blkt}$	0.30***	0.30***	0.30***	0.30***	0.30***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
All-in-$spread_{blk\tau}$	0.66	0.65	0.67	0.66	0.65
	(0.42)	(0.43)	(0.42)	(0.42)	(0.43)
Dual $holding_{blt}$	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
PE $Sponsored_{bt}$	0.02	0.02	0.02	0.02	0.02
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Ln(Number of $BDCs)_{bt}$	-0.02***	-0.02***	-0.02***	-0.01***	-0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bank $financing_{bt}$	-0.02*	-0.02*	-0.02*	-0.02*	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Fixed-effects					
YearQtr-Industry	Yes	Yes	Yes	Yes	Yes
Borrower	Yes	Yes	Yes	Yes	Yes
Seniority	Yes	Yes	Yes	Yes	Yes
LoanType	Yes	Yes	Yes	Yes	Yes
YearQtr-BDC	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	103,395	101,374	103,395	103,395	101,374
Adjusted R^2	0.54	0.54	0.54	0.54	0.54
Dependent variable mean	0.07	0.07	0.07	0.07	0.07

exit. The estimated HRs for PIK range from 0.554 to 0.609 and are statistically significant at the 1% level, implying roughly a 39–45% reduction in the instantaneous exit rate for loans using PIK relative to otherwise comparable loans. Importantly, the magnitude is stable when progressively absorbing heterogeneity via industry and BDC strata, suggesting the relationship is not driven solely by differences in sector composition or lender-specific exit behavior.

The control variables exhibit economically intuitive patterns. Larger loans and loans with longer remaining maturities have lower exit hazards (HRs of 0.821–0.900 for log loan size and 0.736–0.791 for $\log(1 + \text{time-to-maturity})$), consistent with more sizable and longer-dated facilities persisting longer in the panel. Higher all-in yields are also associated with a lower hazard of exit (HRs of 0.048–0.085). In contrast, non-accrual status is not statistically distinguishable from one, indicating limited incremental predictive power for termination once the other covariates and flexible strata are included. Overall, the survival evidence links PIK usage to longer observed loan durations rather than accelerated exits, consistent with PIK operating as a form of evergreening frequently coupled with maturity extensions.

Table A9: Cox Proportional Hazards Regression - Loan-Level Panel

This table reports hazard ratios from Cox proportional hazards regressions estimating the likelihood of loan exit from the sample. The dependent variable is the time (in quarters) until termination, with censoring for relationships that do not end during the observation window. The key explanatory variable is the indicator variable for PIK use. Other covariates control for log loan size, all-in yield, nonaccrual status, and log (1 + time to maturity), all measured at $t-1$. Reported coefficients are hazard ratios (HRs), where values greater than one indicate an increased hazard (shorter time to loan exit) and values less than one indicate a lower hazard (longer time to loan exit). The sample excludes PIK notes. Each specification differs in the inclusion of stratification variables that control for unobserved heterogeneity across origination years, industries, and BDCs. Standard errors are clustered at the borrower level. Significance levels based on the underlying log-coefficient estimates: *(p<0.10), **(p<0.05), ***(p<0.01) (***).

	Hazard Ratios		
	(1)	(2)	(3)
$\text{PIK}_{blk,t-1}$	0.586***	0.608***	0.554***
	(0.045)	(0.046)	(0.054)
$\text{All-in-yield}_{blk,t-1}$	0.067***	0.049***	0.086***
	(0.340)	(0.345)	(0.443)
$\text{Non-Accrual}_{blk,t-1}$	1.027	1.015	1.014
	(0.055)	(0.056)	(0.065)
$\text{Ln(Loan Size}_{blk,t-1})$	0.897***	0.900***	0.822***
	(0.005)	(0.006)	(0.007)
$\text{Ln(1+Time-to-Maturity}_{blk,t-1})$	0.792***	0.791***	0.737***
	(0.014)	(0.014)	(0.017)
Strata (Origination Year)	Yes	Yes	Yes
Strata (Industry)		Yes	Yes
Strata (BDC)			Yes
Observations	332,587	302,220	302,220

References

Haque, S., S. Mayer, and I. Stefanescu (2024): “Private Debt versus Bank Debt in Corporate Borrowing,” *Working Paper*.